Essays on Micro-Level Consumption Behavior and Open Economy Macroeconomics

Seungki Hong

Submitted in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy
under the Executive Committee
of the Graduate School of Arts and Sciences

COLUMBIA UNIVERSITY

2021

Abstract

Essays on Micro-Level Consumption Behavior and Open Economy Macroeconomics

Seungki Hong

This dissertation finds significant differences in the micro-level household consumption behavior between emerging and developed economies, disentangles multiple possible explanations for these differences, and evaluates their macroeconomic implication on business cycles.

The first chapter estimates the marginal propensity to consume (MPC) out of transitory income shocks using micro data for an emerging economy. To this end, I employ a nationally representative Peruvian household survey. Two striking differences emerge when the Peruvian MPC estimates are compared with U.S. MPC estimates obtained by the same method. First, the mean MPC of Peruvian income deciles is much higher than that of U.S. deciles. Second, within-country MPC heterogeneity over the deciles is substantially stronger in Peru than in the U.S.

The second chapter studies the driving factor for the MPC differences between Peru and the U.S. I begin by exploring three possible explanations for the stronger MPC heterogeneity in Peru through the lens of a standard precautionary saving model: liquidity constraints, consumption front-loading behavior, and heterogeneous interest rates. Then, I disentangle these possible explanations by examining relevant data patterns appearing in the micro data. Specifically, participation rates in borrowing activities and consumption growth rate patterns of the income deciles suggest that liquidity constraints drive the stronger MPC heterogeneity in Peru. Then, I decompose the cross-country MPC gap into the component driven by liquidity constraints and the component caused by factors unrelated to liquidity constraints. To this end, I delineate a top income group unaffected by liquidity constraints in each country by conducting an MPC homogeneity test and evaluate its MPC. I find that liquidity constraints are also important for explaining the higher mean MPC in Peru.

The third chapter makes a first attempt to study emerging market business cycles in a heterogeneous-agent open economy model. A central question in open economy macroeconomics is how to explain excess consumption volatility in emerging economies. This chapter argues that to un-

derstand this phenomenon, it is important to take into account households' idiosyncratic income risk, precautionary saving, and MPCs. Financial frictions determining asset liquidity in the model are calibrated such that MPCs are as high as empirical estimates from Peruvian micro data, which are substantially greater than the U.S. MPC estimates. I then estimate the model using macro data and Bayesian methods. The model captures the observed excess consumption volatility well. To highlight the importance of high-MPC households in driving this result, I show that excess consumption volatility disappears when households are counterfactually replaced with those exhibiting U.S. MPCs. High-MPC households contribute to consumption volatility through i) their strong consumption response to resource fluctuations and ii) large consumption reduction when assets become more illiquid. The transmission mechanisms of trend shocks and interest rate variations that previous studies use to explain excess consumption volatility are dampened because households significantly deviate from the permanent income hypothesis, on which these mechanisms crucially depend.

Table of Contents

List of Tables

List of Figures

Acknowledgements

I am highly indebted to my advisor, Martin Uribe. The whole journey of my doctoral research can be summarized as countless repetitions of me facing a new problem, sitting down and discussing with him in his office, and making a progress. Without his time and effort devoted to advising my research, I would not have been able to complete this dissertation. I am deeply grateful to Stephanie Schmitt-Grohe and Andres Drenik for their constant feedback, advice, and support. Stephanie's meticulous reviews and suggestions always provided me invaluable opportunities to make significant improvement that I would have missed. Discussions with Andres guided me on how to deal with micro data and heterogeneous-agent models. I also sincerely thank the other members of my dissertation committee, Hassan Afrouzi and Christian Moser for their attentive advice and support throughout the job market and dissertation process.

My dissertation also greatly benefited from comments and feedback provided by Nils Gornemann, Emilien Gouin-Bonenfant, Jennifer La'O, Tommaso Porzio, Jesse Schreger, Shang-Jin Wei, Michael Woodford, and Stephen Zeldes.

I am also grateful to my classmates, Paul Bouscasse, Anastasia Burya, Christopher Cotton, Dong Woo Hahm, Jay Hyun, Yoon Jo, Meeroo Kim, Paul Koh, Sang Hoon Kong, Rui Mascarenhas, Seunghoon Na, Felipe Netto, Gustavo Pereira, Shogo Sakabe, Yeji Sung, Ken Teoh, Mengxue Wang, Xiao Xu, Lizi Yu, and all the participants of the Economic Fluctuations Colloquium at Columbia University. Numerous discussions that I have had with them over coffees and sandwiches since the beginning of my Ph.D. years have fundamentally shaped how I think through the lens of economics.

Above all, I would like to express my deepest thanks to my wife, Soyoung Kim, for her unconditional love and support, which enabled me to keep moving forward even at the most frustrating moments during my Ph.D. years. I also sincerely thank my parents, Jongdae Hong and Jinsook Oh, for their infinite love and support.

To Soyoung and Eunwoo

Chapter 1: MPCs in Emerging Economies: Evidence from Peru

1.1 Introduction

Estimating the marginal propensity to consume out of transitory income shocks (MPC, hereafter) is essential for evaluating policy effects and testing economic theories such as the permanent income hypothesis. Recently, the estimation of the MPC has also become crucial in the growing literature on the importance of micro heterogeneity on macroeconomic dynamics.[1]

Although most MPC estimation exercises have been conducted in the context of developed economies, there also exist several studies that estimate MPCs in emerging economies.[2] However, these MPC estimates have important limitations to be used in the context of international macroeconomics. First, these studies employ an experimental/quasi-experimental approach, which exploits certain episodes with particular income shocks.[3] This approach is not suitable for cross-country MPC comparison between emerging and developed economies because it is difficult to find comparable experimental/quasi-experimental settings in the two economies. Second, samples used in these studies are usually not nationally representative. It is because under the experimental/quasi-experimental approach, the sample needs to be restricted to those eligible for receiving the income shocks that this approach exploits.[4] [5] This limitation could be particularly problematic when we

[1]See Kaplan, Moll, and Violante (2018), Auclert (2019), Auclert, Rognlie, and Straub (2018), and Auclert, Rognlie, and Straub (2020), for example.

[2]See Paxson (1992), Haushofer and Shapiro (2016), and Egger, Haushofer, Miguel, Niehaus, and Walker (2019), for example.

[3]For example, Paxson (1992) uses rainfall shocks in rural Thailand, and Haushofer and Shapiro (2016) and Egger et al. (2019) use randomized cash transfers in rural Kenya.

[4]For example, Paxson (1992)'s sample is composed of rice farmers in rural Thailand, and Haushofer and Shapiro (2016)'s and Egger et al. (2019)'s samples are composed of poor households in a small study district within rural Kenya.

[5]Among those focusing on developed economies, there exist studies that employ the quasi-experimental approach but still use a nationally representative sample. Johnson, Parker, and Souleles (2006) and Parker, Souleles, Johnson, and McClelland (2013) estimate MPCs for U.S. households using tax rebates in 2001 and economic stimulus payments in 2008, respectively. Their samples are nationally representative because most U.S. households were eligible for the tax rebates and the stimulus payments.

need MPC estimates to discipline a macroeconomic model.

This chapter aims to overcome these limitations by estimating MPC with a semi-structural method devised by Blundell, Pistaferri, and Preston (2008) and a nationally representative sample of an emerging economy. Blundell et al. (2008)'s method imposes a theory-guided covariance structure on joint dynamics of income and consumption. This approach is suitable for cross-country MPC comparison between emerging and developed economies because the same econometric procedure can be applied to both economies' micro data. I apply this method to the sample from a Peruvian household survey, Encuesta Nacional de Hogares (ENAHO)[6], which is nationally representative and also meets all the data requirements of the method. Specifically, I estimate the MPC of each income decile of the sample.

When the Peruvian MPC estimates are compared with U.S. MPC estimates obtained by the same method, two striking differences emerge. First, the MPCs of the Peruvian deciles are substantially higher overall than those of the U.S. deciles. The mean MPC of the Peruvian deciles (63.2 percent) is 54.3 percentage points higher than that of the U.S. deciles (8.9 percent). Second, in both countries, lower income deciles tend to have higher MPCs, but the within-country MPC heterogeneity over the income deciles is substantially stronger in Peru than in the U.S. The MPC of the bottom decile (94.2 percent) is 64.3 percentage points higher than that of the top decile (29.9 percent) in Peru, while in the U.S., the MPC of the bottom decile (16.0 percent) is 12.4 percentage points higher than that of the top decile (3.6 percent).

Methodologically, this chapter employs one of the main approaches from the extensive literature on MPC estimation. In this literature, the key to estimating the MPC is to identify unexpected transitory income shocks and to measure consumption responses to such shocks. To this end, three approaches have been widely accepted: (i) exploiting experimental/quasi-experimental settings, (ii) imposing a theory-guided covariance structure on joint dynamics of income and consumption, and (iii) directly using answers to survey questions asking how much households would spend out of hypothetical income shocks. Well-known works in each of the approaches include Johnson et al.

[6]Instituto Nacional de Estadística e Informática (2004-2016)

(2006) and Parker et al. (2013), Paxson (1992), Haushofer and Shapiro (2016), Egger et al. (2019) for the first approach, Blundell et al. (2008) and Kaplan, Violante, and Weidner (2014b) for the second approach, and Jappelli and Pistaferri (2014) for the third approach, among many others. As explained above, I use the second approach in this chapter because it is suitable for obtaining MPC estimates from a nationally representative sample and comparing the estimates across countries.

Chapter 2 and chapter 3 examine causes and consequences of the findings of chapter 1, respectively. In chapter 2, I study the driving factor for the differences between Peruvian and U.S. MPCs. Specifically, I explore possible explanations for the cross-country MPC differences and disentangle them by examining relevant patterns in the micro data. In chapter 3, I evaluate the macroeconomic implication of the MPC differences between Peru and the U.S. on their business cycle differences through the lens of a heterogeneous-agent open economy model.

The remainder of this chapter is organized as follows. In section 1.2, I discuss the key equation for the MPC estimation and the underlying model from which the equation is derived. In particular, I extend the underlying model of Blundell et al. (2008) by introducing liquidity constraints, verify that the key identification equation does not change, and discuss how the different degrees of liquidity constraints affect consumption responsiveness to transitory income shocks. Section 1.3 discusses the micro data sets used in the estimation and how I process them. Section 1.4 reports the results of the MPC estimation. Section 1.5 concludes this chapter.

1.2 The Underlying Model and MPC Estimation

The key equation for the MPC estimation of this chapter is a first-order-approximated consumption growth function derived from a version of the standard precautionary-saving models. I begin by presenting the model. After that, I discuss the first-order-approximated consumption growth function derived from the model. The derivation, which I provide in Appendix A.1, is nearly identical to that of Blundell et al. (2008), except for the part that deals with liquidity constraints, which are absent in their underlying model. Then, I discuss how to estimate the MPC using the consumption growth function and the imposed income process.

1.2.1 The Underlying Model

In period t, each household i solves the following optimization problem.

$$\max_{\{C_{i,t+j},A_{i,t+j}\}_{j=0}^{J_{i,t}}} E\left[\sum_{j=0}^{J_{i,t}} \beta^j e^{(Z'_{i,t+j}\varphi^p_{t+j})} \frac{C_{i,t+j}^{1-\sigma}}{1-\sigma}\middle|\mathbf{S}_{i,t}\right]$$

$$s.t.$$

$$C_{i,t+j} + A_{i,t+j} = Y_{i,t+j} + (1 + r_{t+j-1})A_{i,t+j-1}, \quad 0 \le j \le J_{i,t}, \tag{SBC}$$

$$A_{i,t+j} \ge 0, \quad 0 \le j \le J_{i,t} - 1, \tag{LQC}$$

$$A_{i,t+J_{i,t}} \ge 0 \tag{NPG}$$

in which $J_{i,t}$ denotes the remaining periods of household i's lifetime after period t, $\mathbf{S}_{i,t}$ denotes the state vector of household i, $Z_{i,t+j}$ denotes a vector of dummy variables for observable characteristics of household i in period $t+j$, $e^{(Z'_{i,t+j}\varphi^p_{t+j})}$ denotes household i's preference shift in period $t+j$, $C_{i,t+j}$ denotes real consumption of household i in period $t+j$, $A_{i,t+j}$ denotes household i's one-period asset purchased in period $t+j$, r_{t+j} denotes the real interest rate associated with asset $A_{i,t+j}$, and $Y_{i,t+j}$ denotes household i's disposable income in period $t+j$. (SBC) represents sequential budget constraints, (LQC) represents liquidity constraints, and (NPG) represents the no-Ponzi-game constraint that households face.

As in Blundell et al. (2008) and Kaplan et al. (2014b), I assume that each household i's log real income $\log Y_{i,t}$ is composed of three components: a component explained by household i's observable characteristics and time $Z'_{i,t}\varphi^y_t$, a permanent component $P_{i,t}$, and a transitory component

$\epsilon_{i,t}$. Specifically, I assume

$$\log Y_{i,t} = Z'_{i,t}\varphi^y_t + P_{i,t} + \epsilon_{i,t},$$

$$P_{i,t} = P_{i,t-1} + \zeta_{i,t},$$

$$\zeta_{i,t} \sim_{iid} (0, \sigma^2_{pm}), \quad \epsilon_{i,t} \sim_{iid} (0, \sigma^2_{tr}), \quad (\zeta_{i,t})_t \perp (\epsilon_{i,t})_t, \quad \text{and}$$

$$(Z_{i,t})_t \perp (\zeta_{i,t}, \epsilon_{i,t})_t$$

in which $(x_t)_t$ represents time series $(\cdots, x_{t-2}, x_{t-1}, x_t, x_{t+1}, x_{t+2}, \cdots)$.

Let $y_{i,t}$ denote the unpredictable component of log income:

$$y_{i,t} := \log Y_{i,t} - Z'_{i,t}\varphi^y_t = P_{i,t} + \epsilon_{i,t}.$$

Then, we have

$$\Delta y_{i,t} = \zeta_{i,t} + \epsilon_{i,t} - \epsilon_{i,t-1}. \tag{1.1}$$

The vector of observable characteristics $Z_{i,t}$ appears in two places in the model: one in the preference shift $Z'_{i,t}\varphi^p_t$ and the other in the predictable component of income $Z'_{i,t}\varphi^y_t$. They appear in these places to make the model consistent with the data pattern that a sizable portion of income and consumption variations are explained by observable characteristics.[7] Specifically, $Z_{i,t}$ includes dummy variables for education, ethnicity, employment status, region, cohort, household size, number of children, urban area, the existence of members other than heads and spouses earning income, and the existence of persons who do not live with but are financially supported by the household. Among these characteristics, education, ethnicity, employment status, and region are allowed to have time-varying effects.

[7]Some studies such as Guvenen and Smith (2014) do not have these terms in the model but instead assume that the residuals of income and consumption after controlling for observable characteristics are income and consumption of per-adult equivalent units, and the residuals should be explained by the model. This alternative approach does not affect the estimation of Blundell et al. (2008)'s partial insurance parameters but affects which consumption-to-income ratio to be multiplied in converting the partial insurance parameters to MPC. I report the MPC estimates under this alternative approach in Appendix A.4.8. The main findings do not change.

Let $Z'_{i,t}\varphi^p_t$ and $Z'_{i,t}\varphi^y_t$ be

$$Z'_{i,t}\varphi^p_t = [(Z^1_{i,t})', (Z^2_{i,t})'] \begin{bmatrix} \varphi^{p1}_t \\ \varphi^{p2} \end{bmatrix}, \quad Z'_{i,t}\varphi^y_t = [(Z^1_{i,t})', (Z^2_{i,t})'] \begin{bmatrix} \varphi^{y1}_t \\ \varphi^{y2} \end{bmatrix}$$

in which $Z^1_{i,t}$ and $Z^2_{i,t}$ are the vectors of dummies for household characteristics with time-varying effects and time-invariant effects, respectively, φ^{p1}_t and φ^{p2} are the elements of φ^p_t associated with $Z^1_{i,t}$ and $Z^2_{i,t}$, respectively, and φ^{y1}_t and φ^{y2} are the elements of φ^y_t associated with $Z^1_{i,t}$ and $Z^2_{i,t}$, respectively. The model is general enough to incorporate aggregate uncertainty by allowing $(\varphi^{p1}_t)_t$ and $(\varphi^{y1}_t)_t$ to be stochastic.

The stochastic processes $(Z_{i,t})_t$, $(\zeta_{i,t})_t$, $(\epsilon_{i,t})_t$, $(\varphi^{p1}_t)_t$, $(\varphi^{y1}_t)_t$, $(r_t)_t$ are all exogenous in the model. I assume that households' idiosyncratic income shocks are independent of other exogenous variables:

$$(\zeta_{i,t}, \epsilon_{i,t})_t \perp (Z_{i,t}, \varphi^{p1}_t, \varphi^{y1}_t, r_t)_t.$$

Moreover, I assume that $(Z_{i,t})_t$ follows a Markov chain with transition probabilities that can be affected by aggregate states. Then, $(Z_{i,t})_t$ satisfies

$$P(Z_{i,t+j}|\mathbf{S}_{i,t}) = P(Z_{i,t+j}|Z_{i,t}, \mathbf{S}^{agg}_t), \quad j \geq 0$$

in which $\mathbf{S}^{agg}_t$ denotes the aggregate state of the economy.

In the model, household i's state vector $\mathbf{S}_{i,t}$ is composed of individual state $\mathbf{S}^{ind}_{i,t}$ and aggregate state $\mathbf{S}^{agg}_t$ as follows.

$$\mathbf{S}_{i,t} = (\mathbf{S}^{ind}_{i,t}, \mathbf{S}^{agg}_t),$$
$$\mathbf{S}^{ind}_{i,t} = \left(A_{i,t-1}, Z_{i,t}, P_{i,t}, \epsilon_{i,t}\right), \quad \mathbf{S}^{agg}_t = \left((\varphi^{p1}_{t-j})_{j\geq 0}, (\varphi^{y1}_{t-j})_{j\geq 0}, (r_{t-j})_{j\geq 0}\right)$$

in which $(x_{t-j})_{j\geq 0} := (x_t, x_{t-1}, x_{t-2}, \cdots)$ denotes the history of time series $(x_s)_s$ up to time t.[8]

[8]The reason why $\mathbf{S}^{agg}_t$ includes the whole history of exogenous aggregate variables is because I do not specify their processes. If I assume that $(r_t)_t$ follows an AR(1) process and has no effect on other aggregate variables, for

Given the assumptions on the exogenous processes, equation '$\log Y_{i,t} = Z'_{i,t}\varphi^y_t + y_{i,t}$' is equivalent to the following decomposition.

$$\log Y_{i,t} = E[\log Y_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t] + \left\{\log Y_{i,t} - E[\log Y_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t]\right\},$$
$$E[\log Y_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t] = Z'_{i,t}\varphi^y_t, \quad \log Y_{i,t} - E[\log Y_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t] = y_{i,t}.$$

In the same way, any variable $x_{i,t}$ can be decomposed as follows:

$$x_{i,t} = E[x_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t] + \left\{x_{i,t} - E[x_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t]\right\},$$
$$E[x_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t] = Z_{i,t}\varphi^x_t, \quad x_{i,t} - E[x_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t] = x_{i,t} - Z_{i,t}\varphi^x_t$$

for some φ^x_t, of which elements corresponding to $Z^1_{i,t}$ are time-varying. From this point on, I describe $E[x_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t]$ as 'part of $x_{i,t}$ explained (or picked up) by $Z_{i,t}$ and time' or 'predictable component of $x_{i,t}$', and $\left\{x_{i,t} - E[x_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t]\right\}$ as 'part of $x_{i,t}$ unexplained (or not picked up) by $Z_{i,t}$ and time' or 'unpredictable component of $x_{i,t}$'. If $x_{i,t} = E[x_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t]$, I describe this equation as '$x_{i,t}$ is explained (or picked up) by Z_{it} and time'.

Equations (1.2), (1.3), (1.4), and (1.5) below constitute the optimality conditions of the model.

$$e^{(Z'_{i,t+j}\varphi^p_{t+j})}C^{-\sigma}_{i,t+j} = \beta(1 + r_{t+j})E_{t+j}\left[e^{(Z'_{i,t+j+1}\varphi^p_{t+j+1})}C^{-\sigma}_{i,t+j+1}\right] + \mu_{i,t+j}, \ 0 \le j \le J_{i,t} - 1, \tag{1.2}$$

$$\mu_{i,t+j} \ge 0, \quad A_{i,t+j} \ge 0, \quad \mu_{i,t+j}A_{i,t+j} = 0, \quad 0 \le j \le J_{i,t} - 1, \tag{1.3}$$

$$A_{i,t+J_{i,t}} = 0, \quad \text{and} \tag{1.4}$$

$$\sum_{j=0}^{J_{i,t}-s} Q_{t+s,t+s+j}C_{i,t+s+j} = \sum_{j=0}^{J_{i,t}-s} Q_{t+s,t+s+j}Y_{i,t+s+j} + (1 + r_{t+s-1})A_{i,t+s-1}, \ 0 \le s \le J_{i,t} \tag{1.5}$$

in which

$$Q_{t,t+j} = \begin{cases} 1 & \text{if } j = 0, \\ \frac{1}{(1+r_t)\cdots(1+r_{t+j-1})} & \text{if } j \ge 1 \end{cases}$$

example, $\mathbf{S}^{agg}_t$ needs to include only r_t, not the whole history $(r_{t-j})_{j\ge0}$.

and $\mu_{i,t+j}$ is the Lagrangian multiplier associated with the liquidity constraint in period $t+j$.

The definition of 'households being liquidity-constrained in period $t+j$' is '$\mu_{i,t+j} > 0$' in this chapter. Equation (1.2) shows that the ratio between today's marginal utility and tomorrow's expected marginal utility is greater than what the Euler equation would dictate when $\mu_{i,t+j}$ is strictly positive. This occurs because households cannot transform their future resources into current consumption completely enough to smooth consumption when they are currently liquidity-constrained.

1.2.2 The Consumption Growth Function

Let $Z'_{i,t}\varphi^c_t := E(\log C_{i,t}|Z_{i,t}, \mathbf{S}^{agg}_t)$ be the component of log consumption explained by $Z_{i,t}$ and time and $c_{i,t} := \log C_{i,t} - Z'_{i,t}\varphi^c_t$ be the component unexplained by them.[9] The consumption growth function used throughout the empirical analyses of this chapter is the following equation.

$$\Delta c_{i,t} = \tilde{\mu}_{i,t-1} + \phi^{PIH}_{i,t}\zeta_{i,t} + \psi^{PIH}_{i,t}\epsilon_{i,t} + \tilde{M}_{i,t} + \xi_{i,t}. \tag{1.6}$$

The consumption growth function (1.6) is derived by first-order-approximating the optimality conditions (1.2) and (1.5).[10] (See Appendix A.1 for the derivation.) Therefore, each term in the equation has a structural interpretation.

$\phi^{PIH}_{i,t}\zeta_{i,t}$ and $\psi^{PIH}_{i,t}\epsilon_{i,t}$ are the consumption responses to income shocks that households would make if liquidity constraints were not imposed in the model. For example, Blundell et al. (2008) consider the same model but without liquidity constraints. In such a model, households' consumption decisions follow the permanent income hypothesis (PIH) with CRRA utilities. From the

[9]Note that $Z'_{i,t}\varphi^c_t$ is not equal to $Z'_{i,t}\varphi^p_t$ because the optimal consumption path is affected not only by the preference shift but also by many other factors. For example, interest rates affect the intertemporal allocation of consumption. Moreover, $Z_{i,t}$ affects the expectation error in equation (1.2). See Appendix A.1 for details.

[10]The underlying model features nonlinearity generated by the liquidity constraints. In the system of equations (1.2), (1.3), (1.4), and (1.5), the nonlinearity manifests through $\mu_{i,t+j}$, $0 \le j \le J_{i,t} - 1$. The first-order approximation implemented to derive equation (1.6) preserves the nonlinearity because any term including $\mu_{i,t+j}$ is not approximated.

model, they derive the following consumption function.

$$\Delta c_{i,t} = \phi_{i,t}^{PIH}\zeta_{i,t} + \psi_{i,t}^{PIH}\epsilon_{i,t} + \xi_{i,t}. \tag{1.7}$$

As a result of imposing the liquidity constraints in my model, equation (1.6) has two more terms, $\tilde{\mu}_{i,t-1}$ and $\tilde{M}_{i,t}$, compared to equation (1.7). Term $\tilde{\mu}_{i,t-1}$ is the component of $\{-(1/\sigma)\log(1-\hat{\mu}_{i,t-1})\}$ unexplained by the history of observable characteristics and aggregate states in which $\hat{\mu}_{i,t-1} := \mu_{i,t-1}/(e^{(Z'_{i,t-1}\varphi^p_{t-1})}C^{-\sigma}_{i,t-1})$ is the shadow cost of the liquidity constraint in terms of consumption goods in period $t-1$. Therefore, the more household i is constrained in period $t-1$, the greater the value of $\tilde{\mu}_{i,t-1}$ is. Term $\tilde{\mu}_{i,t-1}$ appearing on the right-hand side of equation (1.6) shows that when households are liquidity-constrained in the current period $t-1$, they cannot transform their future resources into current consumption completely enough to smooth consumption, and therefore, their consumption jumps in the following period t.

Term $\tilde{M}_{i,t}$ is the part of M_t unexplained by the history of observable characteristics and aggregate states, and M_t is the weighted sum of $[E_t\log(1-\hat{\mu}_{i,t+j}) - E_{t-1}\log(1-\hat{\mu}_{i,t+j})]$'s for $0 \leq j \leq J_{i,t}-1$, which is the expectation change in the effects of the current and future liquidity constraints on the current consumption growth. Term $\tilde{M}_{i,t}$ is positively correlated with transitory income shock $\epsilon_{i,t}$ because it relaxes the current liquidity constraint for currently constrained households and reduces the precautionary-saving motive for households that are currently unconstrained but are concerned about being constrained in the future. The correlation becomes stronger as households approach the liquidity constraint. If households are far away from the liquidity constraint such that the probability of hitting the constraint in the future is negligible, the correlation should be close to zero.

The last term $\xi_{i,t}$ captures the part of $\Delta\log C_{i,t}$ that is explained by the history of observable characteristics and aggregate states but is not picked up by $\Delta Z'_{i,t}\varphi^c_t$. $E\xi_{i,t} = 0$ holds by construction, and $\xi_{i,t}$ can be autocorrelated. Since $(\zeta_{i,t}, \epsilon_{i,t})_t \perp (Z_{i,t}, \mathbf{S}^{agg}_t)_t$, we have $(\xi_{i,t})_t \perp (\zeta_{it}, \epsilon_{it})_t$.[11]

[11] These features of $\xi_{i,t}$ remain unchanged even when we allow $\xi_{i,t}$ to include measurement errors that are mean-zero, autocorrelated, but uncorrelated with $(\zeta_{i,t}, \epsilon_{i,t})_t$.

1.2.3 MPC Estimation

I estimate the MPC of each income decile in Peru and the U.S., separately. As in Blundell et al. (2008), I assume the partial insurance parameters under PIH, $\phi_{i,t}^{PIH}$ and $\psi_{i,t}^{PIH}$ are constant within each group but can vary across different groups. Under this assumption, equation (1.6) becomes

$$\Delta c_{i,t} = \tilde{\mu}_{i,t-1} + \phi_G^{PIH} \zeta_{i,t} + \psi_G^{PIH} \epsilon_{i,t} + \tilde{M}_{i,t} + \xi_{i,t}, \quad (i,t) \in G \tag{1.8}$$

in which G denotes a group of observation (i,t)'s.

As we shall see in section 1.3, households are interviewed annually and one quarterly income and consumption are available per interview in the Peruvian data. Thus, we have year-over-year growth of quarterly consumption and income for the Peruvian sample. On the other hand, households are interviewed biannually and one annual income and consumption are available per interview in the U.S. data. Therefore, we have two-year-over-two-year growth of annual consumption and income for the U.S. sample. To examine equations (1.1) and (1.8) with these data, I sum each of the equations over multiple periods as follows.

$$\Delta^K y_{i,t} = \sum_{j=0}^{K-1} \zeta_{i,t-j} + \epsilon_{i,t} - \epsilon_{i,t-K}, \tag{1.9}$$

$$\begin{aligned} \Delta^K c_{i,t} = & \sum_{j=0}^{K-1} \tilde{\mu}_{i,t-j-1} + \phi_G^{PIH} \sum_{j=0}^{K-1} \zeta_{i,t-j} + \psi_G^{PIH} \sum_{j=0}^{K-1} \epsilon_{i,t-j} \\ & + \sum_{j=0}^{K-1} \tilde{M}_{i,t-j} + \sum_{j=0}^{K-1} \xi_{i,t-j}, \quad (i,t) \in G \end{aligned} \tag{1.10}$$

in which $\Delta^K x_t := x_t - x_{t-K}$ for time series $(x_t)_t$. For the Peruvian sample, I set the period as a quarter and $K = 4$. For the U.S. sample, I set the period as a year and $K = 2$.

As in Blundell et al. (2008) and Kaplan et al. (2014b), I define the partial insurance parameter to transitory income shocks ψ_G for each group G as follows.

$$\psi_G := \frac{cov[\Delta c_{i,t}, \epsilon_{i,t}|(i,t) \in G]}{cov[\Delta y_{i,t}, \epsilon_{i,t}|(i,t) \in G]}. \tag{1.11}$$

Parameter ψ_G is the elasticity of consumption with regard to income when the income change is caused by a transitory income shock. When the grouping of observation (i,t)'s is independent of $\epsilon_{i,t}$, we can obtain

$$\psi_G = \psi_G^{PIH} + \frac{cov[\epsilon_{i,t}, \tilde{M}_{i,t}|(i,t) \in G]}{var[\epsilon_{i,t}|(i,t) \in G]} \tag{1.12}$$

by substituting equations (1.1) and (1.8) into equation (1.11). Note that ψ_G is equal to ψ_G^{PIH} when the liquidity constraints are removed from the model.

When the grouping of observation (i,t)'s is independent of $(\zeta_{i,t+j}, \epsilon_{i,t+j})_{j\geq 0}$ (the income shocks from period t onward), we can derive

$$\psi_G = \frac{cov[\Delta^K c_{it}, \Delta^K y_{i,t+K}|(i,t) \in G]}{cov[\Delta^K y_{it}, \Delta^K y_{i,t+K}|(i,t) \in G]}, \quad K \geq 1 \tag{1.13}$$

from equations (1.9) and (1.10).[12] Intuitively, ψ_G can be identified by running an IV regression in which $\Delta^K c_{i,t}$ is the dependent variable, $\Delta^K y_{i,t}$ is the endogenous regressor, and $\Delta^K y_{i,t+K}$ is the instrumental variable.

I use equation (1.13) to identify ψ_G. I group observation (i,t)'s based on their unpredictable component of income in period $t-K$, $y_{i,t-K}$, so that the grouping is independent of $(\zeta_{i,t+j}, \epsilon_{i,t+j})_{j\geq 0}$. Since ψ_G is an elasticity, I identify the MPC out of a transitory income shock by multiplying ψ_G by the ratio of the average consumption to the average income of group G in period $t-K$ as follows.

$$MPC_G = \psi_G \frac{E[C_{i,t-K}|(i,t) \in G]}{E[Y_{i,t-K}|(i,t) \in G]}. \tag{1.14}$$

[12]We can also verify from equations (1.9) and (1.10) that Blundell et al. (2008)'s formula for the partial insurance parameter to permanent income shocks, $\phi = \frac{cov(\Delta^K c_{it}, \Delta^K y_{i,t-K} + \Delta^K y_{it} + \Delta^K y_{i,t+K})}{cov(\Delta^K y_{it}, \Delta^K y_{i,t-K} + \Delta^K y_{it} + \Delta^K y_{i,t+K})}$ provides a biased estimate in the presence of liquidity constraints. This is consistent with Kaplan and Violante (2010)'s finding that Blundell et al. (2008)'s estimator for ϕ is biased while their estimator for ψ is unbiased when data are simulated from a model with borrowing constraints.

Let $\kappa_G := \frac{E[C_{i,t-K}|(i,t)\in G]}{E[Y_{i,t-K}|(i,t)\in G]}$. To estimate MPC_G using equations (1.13) and (1.14), I estimate $(\kappa_G, \alpha_G, \psi_G)$ from the following moment conditions using the GMM method.

$$\begin{aligned} E[\kappa_G Y_{i,t-K} - C_{i,t-K}|(i,t) \in G] = 0, \\ E[\Delta^K c_{i,t} - \alpha_G - \psi_G \Delta^K y_{i,t}|(i,t) \in G] = 0, \quad \text{and} \\ E[\Delta^K y_{i,t+K}(\Delta^K c_{i,t} - \alpha_G - \psi_G \Delta^K y_{i,t})|(i,t) \in G] = 0. \end{aligned} \tag{1.15}$$

Standard errors are clustered within each household.[13] Once we have the GMM estimates and the variance-covariance matrix of $(\kappa_G, \alpha_G, \psi_G)$, we can obtain the estimate of MPC_G and its standard error using equation (1.14) or, equivalently,

$$MPC_G = \psi_G \kappa_G.$$

Since one period is a quarter for the Peruvian sample and a year for the U.S. sample, equation (1.14) yields quarterly MPCs for Peru and annual MPCs for the U.S. To compare the quarterly MPC estimates with the annual MPC estimates, I convert the quarterly MPCs of Peruvian households to annual MPCs by adopting Auclert (2019)'s conversion formula, which the author uses for the same purpose of comparing quarterly MPC estimates with annual MPC estimates. The conversion formula is

$$MPC_G^A = 1 - (1 - MPC_G^Q)^4 \tag{1.16}$$

in which MPC_G^A denotes the annual MPC and MPC_G^Q denotes the quarterly MPC of group G.[14] [15]

[13]The standard error clustering within each household is important because (i) the error term $(\Delta^K c_{i,t} - \alpha_G - \psi_G \Delta^K y_{i,t})$ is autocorrelated as it includes $\sum_{j=0}^{K-1} \tilde{\mu}_{i,t-j-1}$ and $\sum_{j=0}^{K-1} \xi_{i,t-j}$, and (ii) the instrumental variable $\Delta^K y_{i,t+K}$ of observation (i,t) can also be correlated with the error term of observation $(i, t+K)$.

[14]Auclert (2019) derives equation (1.16) under the assumption that the quarterly consumption response in period $t + j$ to a shock in period t decays exponentially in j and the interest rate is close to zero. The author finds that this conversion formula is a good approximation in partial equilibrium Bewley models.

[15]The standard errors are also converted using equation (1.16) and the Delta method.

1.3 Data

1.3.1 Data Source

The MPC estimation for emerging economies using Blundell et al. (2008)'s method requires a micro dataset that satisfies four requirements. First, the dataset should include both the income and expenditure of households. Second, the dataset should have a panel structure of at least three consecutive surveys. Third, the sample should be representative of a country. Fourth, the dataset should be for an emerging economy. ENAHO is one of the rare datasets, if not the only one, that satisfies all four requirements. It is the major information source of the quantity indices for the final household expenditure in Peru's national accounts (Instituto Nacional de Estadística e Informática, n.d.) and thus is nationally representative and includes detailed categories of household expenditure. Moreover, ENAHO also collects information on detailed sources of household income. ENAHO tracks a subset of annual cross-sectional observations in the following year and possibly more. The panel households are also nationally representative. Most panel households appear two or three times in the data, while the maximum number of appearances is six. I use 2004-2016 waves of ENAHO. These waves give 11 years of consumption and income growth because the survey is annually conducted and there is no panel structure between the 2006 wave and the 2007 wave. Appendix A.2.1 provides more details about ENAHO including its coverage and and non-response rates.

For the MPC comparison between emerging and developed economies, I need another micro dataset that satisfies the first, second, and third conditions discussed above, but for a developed economy. I choose Kaplan et al. (2014b)'s replication dataset for U.S. households[16]. For the purpose of cross-country comparison, their dataset is relevant for two reasons. First, their sample years are not too different from the sample years of the Peruvian dataset I use in this chapter. Specifically, they use the 1999-2011 waves from the Panel Study of Income Dynamics (PSID), which overlap significantly with my Peruvian sample (waves 2004-2016). Second, they prepare

[16]Kaplan, Violante, and Weidner (2014a)

the dataset to estimate Blundell et al. (2008)'s partial insurance parameter with regard to transitory income shocks, which is the same object upon which I base my MPC estimates.

1.3.2 Variable Construction

The baseline consumption measure for both Peruvian and U.S. households includes nondurable goods and a subset of services, as in many other studies on household consumption, such as Attanasio and Weber (1995) and Kocherlakota and Pistaferri (2009). Following these studies, I exclude health and education expenses from the consumption due to their durable nature. I exclude non-purchased consumption such as donations, food stamps, in-kind income, and self-production from the consumption. Including these items does not change the results in any meaningful way, as reported in Appendix A.4.1 and B.2.1. Due to the lack of coverage in the early waves in the U.S. sample, the consumption of U.S. households does not include clothing, recreation, alcohol, and tobacco, while the consumption of Peruvian households includes them. In Appendix A.4.2 and B.2.2, I conduct a robustness check by consistently excluding these expenses from the consumption of Peruvian households and verify that the main findings are robust. The constructed consumption of households in each country is deflated with the Consumer Price Index (CPI) series.

The income measure for both countries is composed of disposable labor income and transfers, as in Blundell et al. (2008) and Kaplan et al. (2014b). Capital income is excluded because we do not want to falsely attribute endogenous capital income changes to unexpected income shocks. In ENAHO, labor income and capital income are not distinguishable in self-employment income. Following Diaz-Gimenez, Quadrini, and Rios-Rull (1997) and Krueger and Perri (2006), I split the self-employment income into a labor income component and a capital income component using the ratio of unambiguous labor income to the sum of unambiguous labor income and unambiguous capital income in the sample.[17] Imputed components of missing income are excluded from the income measure for ENAHO, as these components might blur the identification of income shocks. I cannot do the same for the income of U.S. households, as the imputed income components are not

[17] In my ENAHO sample, the ratio is 0.819. This ratio is slightly lower but quite similar to the ratio in the U.S., 0.864, which Diaz-Gimenez et al. (1997) and Krueger and Perri (2006) use.

distinguishable in Kaplan et al. (2014b)'s dataset. In Appendix A.4.3, I conduct a robustness check by consistently including the imputed components of Peruvian households' income and verify that it does not change the results in any meaningful way. The income of Peruvian households includes two expense items that are also included in their consumption: rental equivalence of housing provided by work (as labor income) and rental equivalence of donated housing (as transfers).[18] On the other hand, the income of U.S. households does not include any expense items that are included in their consumption. In Appendix A.4.4 and B.2.3, I conduct a robustness check by consistently excluding the two expense items from Peruvian households' income and verify that the main findings are robust. The constructed income of households in each country is deflated with the CPI series.

In ENAHO, reference periods vary over both expense items and income items. More importantly, individual households report more than 97 percent (in value) of expense items and income items, respectively, with reference periods shorter than or equal to the previous three months, on average. Given this feature of the data, I construct quarterly consumption and income by excluding expense and income items with reference periods longer than the previous three months. Expense and income items with reference periods shorter than the previous three months are scaled up to the quarterly expense and income, respectively. Since panel households are tracked only annually, we can only obtain the year-over-year growth of quarterly consumption and income from ENAHO. In the PSID, the reference period is fixed to one year, while households are tracked only biannually during the sample years of Kaplan et al. (2014b)'s dataset. Therefore, we can only obtain two-year-over-two-year growth of annual consumption and income from their dataset. [19]

[18]However, the income measure does not include rental equivalence of owned housing because it is categorized as capital income.

[19]Both the PSID and ENAHO are not free from the problem of time inconsistency between the reference period for consumption and that for income. In the PSID, the reference period for income is firmly fixed to a calendar year, but the reference period for consumption can depend on an interpretation, as pointed out by Crawley (2019). For example, the reference period for food consumption in the PSID questionnaire can be interpreted either as average weekly consumption during the reference year of income or as the consumption in the last week of the survey. In the baseline analysis, I accept the former interpretation, as many other studies implicitly do. Under the alternative interpretation, however, the time inconsistency problem arises in such a way that the reference period for income is longer than that for consumption. In ENAHO, the reference periods for both consumption and income are restricted to be no longer than the previous three months, as discussed above. Within these three months, however, the time inconsistency problem exists in both ways: some expense items have longer reference periods than some income items, while some

Appendix A.2.2 provides more details of the variable construction.

1.3.3 Sample Selection

Provided that the empirical analyses of this chapter require multiple appearances by households, it is convenient to define different units of observation for the sake of discussion. I define an observation of a household in *n* consecutive surveys as a type-*n* observation. If a household appears in three consecutive surveys, this household provides three type-1 observations, two type-2 observations, and one type-3 observation.

Sample selection is implemented for either type-1 observations or type-2 observations. When I drop some type-1 observations, type-2 and type-3 observations that contain the dropped type-1 observations are also dropped. When I drop some type-2 observations, type-1 observations that do not have any selected type-2 observations to belong to are also dropped, and type-3 observations that contain the dropped type-2 observations are also dropped.

The sample selection for ENAHO proceeds as follows. First, I begin with type-1 observations that belong to at least one type-2 observation. Second, I drop type-2 observations if the interview months are not matched between the two consecutive surveys. Moreover, there are type-2 observations that are likely to falsely connect two different households. Such type-2 observations are detected and dropped.[20] Type-2 observations are also dropped if the head of the household changes. Third, type-1 observations are dropped if a survey response is categorized as incomplete by interviewers. Fourth, type-1 observations are dropped if the household heads are younger than 25 or older than 65. Fifth, type-1 observations are dropped if any of the observable characteristics needed to control income and consumption are missing. Sixth, type-1 observations are dropped if they have non-positive income or consumption. Seventh, type-1 observations are dropped if they have too much value in imputed income components. Similarly, type-1 observations are dropped if they report too much value in expense items or income items with reference periods longer than

expense items have shorter reference periods than some income items. In a robustness check conducted in Appendix A.4.9, I address this time inconsistency problem using a continuous-time model and find that the main findings are robust to correcting the problem.

[20] Appendix A.2.4 provides details of the procedure.

the previous three months. Eighth, all type-1 observations on households categorized as an income outlier are dropped.[21] This sample selection leaves 47,210 type-1 observations, 21,988 type-2 observations, and 7,509 type-3 observations. Appendix A.2.3 provides more details of the sample selection procedure including how many observations of each type are dropped in each step.

For the U.S. households, I adopt Kaplan et al. (2014b)'s sample selection with only a few minor revisions because their sample selection procedure is similar to mine. Appendix A.2.3 discusses details of the minor revisions and a remaining difference between my sample selection for ENAHO and their sample selection for the PSID, as well as a robustness check regarding the difference.

1.3.4 Income Grouping

I estimate the MPC of each income decile in each country. The income distribution for the deciles is constructed by sorting type-1 observations with their unpredictable component of log real income, $y_{i,t}$. In accordance with the unit time length of each sample (a year for the U.S. sample and a quarter for the Peruvian sample), I sort the U.S. type-1 observations within each calendar year and the Peruvian type-1 observations within each calendar quarter.[22] The survey weights are used to compute the quantile of each observation.

The unit of observation in the MPC estimation is the type-3 observation. The observation that I denote as (i, t) in subsection 1.2.3 is the type-3 observation of household i in period $t - K$, t, and $t + K$ in which $K = 4$ in the Peruvian sample and $K = 2$ in the U.S. sample. The income decile of the type-3 observation is determined by its unpredictable component of log real income in the initial period $t - K$, $y_{i,t-K}$.

My baseline income measure for the Peruvian sample does not include items with reference periods longer than the previous three months and imputed income components, and I drop type-1 observations that have too much value in these components in the sample selection. If the pro-

[21] Income growth is used for the criterion of income outliers. See Appendix A.2.3 for details.

[22] Because I already remove the time-fixed effect when controlling for the predictable components (annually for the U.S. sample, quarterly for the Peruvian sample), it should also be fine to sort unpredictable component of income $y_{i,t}$ in a larger observation pool than the pool of the unit time length. In Appendix A.4.5 and B.2.4, I conduct a robustness check by sorting income in different observation pools and find that the main results are robust.

portion of these components in household income is correlated with the income level, this sample selection can cause a selection bias. Dropping observations with too much value in expense items with reference periods longer than the previous three months can cause the same issue.

To resolve this concern, when constructing the income distribution and determining the income quantiles of the selected observations in the Peruvian sample, I include the dropped observations due to having too much value in income or expense items with reference periods longer than the previous three months or to having too much value in imputed income components. To sort these dropped observations and the selected observations together, I use the unpredictable component of the log real income of a comprehensive income measure that includes not only the baseline measure of income but also the income items with reference periods longer than the previous three months and the imputed components of income. Although these income components are bad because they can blur the measurement of income growth, they are helpful in determining the income quantiles of the selected observations.

1.4 Results

1.4.1 Cross-Country MPC Comparison

Figure 1.1 plots the annual MPC estimates and the 95% confidence intervals of the income deciles in Peru and the U.S.[23] The result shows two striking differences between the two countries' MPCs. First, the MPCs of the Peruvian deciles are substantially higher overall than those of the U.S. deciles. The mean MPC of the Peruvian deciles (63.2 percent) is 54.3 percentage points higher than that of the U.S. deciles (8.9 percent).[24] Second, in both countries, lower income deciles

[23] Appendix A.3 reports the numerical values of the estimates and standard errors in a table for interested readers.

[24] The average U.S. MPC estimate in this chapter, 8.9 percent is in the same ballpark as the estimates of other studies which also apply Blundell et al. (2008)'s method to the PSID. Auclert (2019) estimates the U.S. MPCs of income terciles using the 1999-2013 waves of the PSID and plots them. In the plot, the author's MPC estimates are located around 2 percent, 10 percent, and 13 percent for the top, middle, and bottom terciles, respectively. Blundell et al. (2008) estimates ψ_G (the partial insurance parameter with regard to transitory income shocks, before converting it to MPC by multiplying income-to-consumption ratio) using the 1978-1992 waves of the PSID. Due to the insufficient coverage of expense items in the PSID during their sample period, they impute consumption based on the food demand estimated from the Consumer Expenditure Survey (CEX). They report 5.3 percent as the estimate of ψ_G for the whole sample.

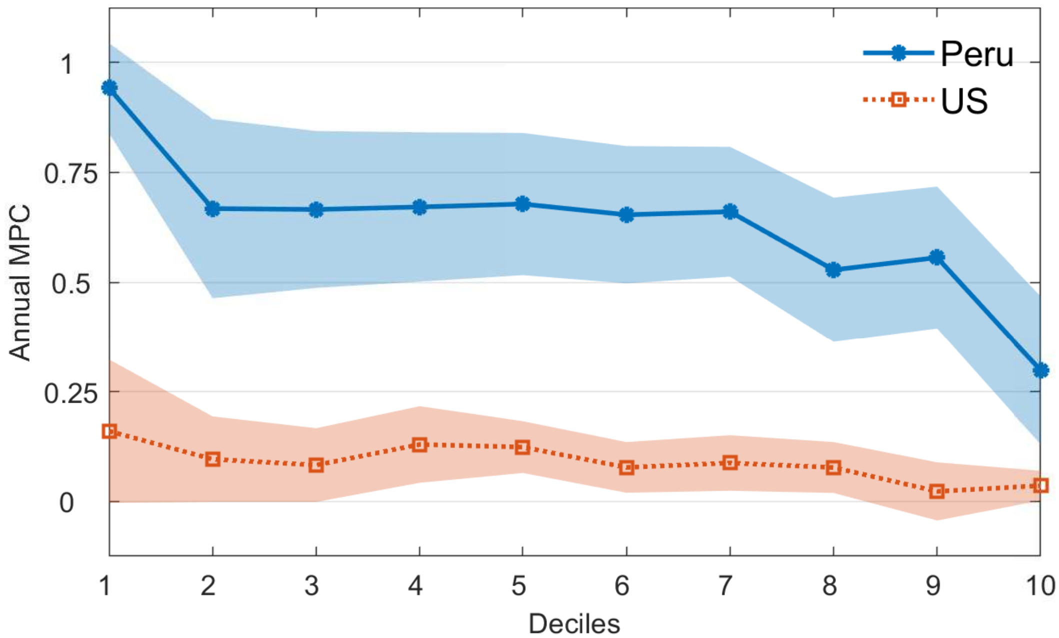


Figure 1.1: Annual MPCs of the Income Deciles in Peru and the U.S.

Notes: In the x-axis, 1 is the bottom decile. Shaded areas represent 95% confidence intervals.

tend to have higher MPC, but the within-country MPC heterogeneity over the income deciles is substantially stronger in Peru than in the U.S. The MPC of the bottom decile (94.2 percent) is 64.3 percentage points higher than that of the top decile (29.9 percent) in Peru, while in the U.S., the MPC of the bottom decile (16.0 percent) is 12.4 percentage points higher than that of the top decile (3.6 percent).

I also find that these two differences consistently appear in an extensive list of robustness checks in Appendix A.4. The list of robustness checks includes (i) alternative measures of consumption and income, (ii) alternative choices of observation pools in sorting income, (iii) alternative underlying models such as a model with persistent (not permanent) income shocks, a model with a subsistence point[25], a model with per-adult equivalent units, and a model in continuous time[26], and (iv) alternative sample selections.

[25] Specifically, I replace the household utility function with the one developed by Stone (1954) and Geary (1950) under which households obtain utility only from consumption beyond a subsistence point.

[26] As Crawley (2019) notes, continuous-time models are useful in dealing with two possible issues in discrete time models: the time aggregation problem and the time inconsistency problem. The time aggregation problem means that a completely transitory shock in a continuous-time process can generate an autocorrelation in a discrete-time process constructed by aggregating the continuous-time process over a specified period. The time inconsistency problem

Figure 1.1 compares the two economies' MPC graphs over the income deciles (not over the income levels). The null hypothesis underlying this comparison is that the U.S. is a scaled-up version of Peru. In other words, the U.S. and Peru follow the same model economy with the same parameter values, but all the quantity variables in the U.S. are proportionally scaled up compared to those in Peru.[27] Under the null hypothesis, we should observe identical MPC graphs over the income deciles between Peru and the U.S. By rejecting this null hypothesis, Figure 1.1 suggests that whenever we discipline a model using MPC estimates, the parameters governing the MPCs in the model should be significantly different between emerging and developed economies, and thus generate a significantly different macroeconomic outcome.

Separately from the relevance of this income-decile comparison in the context of disciplining a model with MPC estimates, it could also be intuitively appealing to compare the MPC estimates over income levels. The null hypothesis underlying this income-level comparison can be formalized as follows: MPC is a function of the Purchasing Power Parity(PPP)-converted level of income $Y_{i,t}$ (including both predictable and unpredictable components) regardless of whether households live in Peru or in the U.S. To test this null hypothesis, in Appendix A.5, I sort households by $Y_{i,t}$ (instead of $y_{i,t}$) to construct income deciles, estimate MPCs of the deciles, and plot them over the x-axis of the PPP-converted group-average values of $Y_{i,t}$. It turns out that the top three deciles in Peru and the bottom three deciles in the U.S. overlap in their PPP-converted income, and in the overlapped region, the mean MPC of the top three deciles in Peru (0.442) is significantly greater than the mean MPC of the bottom three deciles in the U.S. (0.173). This result rejects the null hypothesis that MPC is determined by the PPP-converted level of income.

means that the reference period for consumption could be inconsistent with the reference period for income because of the intended design of a survey, unclear description of the questionnaires, or greater difficulties in recalling memory regarding expenses. As in Crawley (2019), I address these issues using a continuous-time model in Appendix A.4.9.

[27]For the null hypothesis to be not self-contradictory, the model economy under the null hypothesis should be scale-free, *i.e.*, the model dynamics do not change when all quantities are proportionally scaled up. For example, the model in subsection 1.2.1 is scale-free. The model remains scale-free when the lower bound of $A_{i,t}$ in equation (LQC) is replaced with a constant fraction of the household's income. However, the model becomes non-scale-free if the lower bound is replaced with a non-zero constant.

1.5 Conclusion

This chapter estimates the MPC out of transitory income shocks using micro data for an emerging economy, Peru. Methodologically, Blundell et al. (2008)'s semi-structural estimation approach is employed for the estimation. Then, the Peruvian MPC estimates are compared with U.S. MPC estimates obtained by the same method. The comparison yields two main conclusions. First, the mean MPC level of Peru is substantially higher than that of the U.S. Second, within-country MPC heterogeneity in income distribution is substantially stronger in Peru than in the U.S.

Chapter 2 and chapter 3 build on the main findings of chapter 1. In chapter 2, I answer the following question: what drives these cross-country differences in the MPC patterns? Specifically, I examine possible explanations for these differences and disentangle them using relevant data patterns appearing in the micro data. In chapter 3, I evaluate the macroeconomic implication of the MPC gap between Peru and the U.S. on their business cycle differences. To this end, I build a heterogeneous-agent open economy model that can capture realistic degrees of households' MPCs.

Chapter 2: What Drives the Distinct MPC Patterns in Emerging Economies? : Evidence from Peru

2.1 Introduction

In chapter 1, I estimate the marginal propensities to consume out of transitory income shocks (MPCs) using emerging market micro data from Peru and Blundell et al. (2008)'s method. Then, I compare the Peruvian MPC estimates with U.S. MPC estimates obtained by the same method. I report two main findings. First, the mean MPC of Peruvian income deciles is much higher than that of U.S. deciles. Second, within-country MPC heterogeneity over the income deciles is substantially stronger in Peru than in the U.S. In this chapter, I explore possible explanations for these differences and disentangle them by carefully examining relevant data patterns.

I begin with the stronger MPC heterogeneity over the income distribution in Peru than in the U.S. When we see this difference through the lens of the standard incomplete-market precautionary-saving models, there are three possible explanations. First, households in lower income deciles could exhibit higher MPC because they are more likely to be constrained than those in higher income deciles. The likelihood of being constrained could increase substantially faster in Peru than in the U.S. as households move from higher to lower income deciles. Second, households in lower income deciles could exhibit higher MPC in the absence of liquidity constraints when they tend to front-load their consumption more heavily in their consumption path governed by the Euler equation. The tendency of lower-income households to front-load consumption more heavily could be stronger in Peru than in the U.S. Third, even when households' consumption path follows the Euler equation and the degree of front-loading is similar across the income deciles, households in lower income deciles could exhibit higher MPC by facing higher interest rates. The tendency of lower-income households to face higher interest rates could be stronger in Peru than in the U.S.

I disentangle these three theory-guided explanations by examining relevant data patterns. The last explanation with heterogeneous interest rates makes sense only when the effective interest rates used by lower-income households for their consumption-saving decision are borrowing interest rates. In the Peruvian sample, however, the share of households participating in borrowing activities is low (13.3 percent), and this share is even smaller in lower income deciles. Based on this observation, I eliminate the heterogeneous interest rate explanation.

The remaining two explanations, one with liquidity constraints and the other with front-loading behavior, are distinguishable by examining consumption growth rates. Under the explanation with liquidity constraints, households in lower income deciles should exhibit higher consumption growth because when they become constrained, they fail to bring future resources to current consumption, and therefore, their consumption jumps in the following period. Under the explanation with front-loading behavior, households in lower income deciles should exhibit lower consumption growth exactly because they front-load consumption more heavily. Under either one of these explanations, the described pattern of the consumption growth should be stronger in Peru than in the U.S.

The group-average consumption growth of the deciles in Peru and the U.S. exhibit two clear patterns. First, lower income deciles exhibit higher consumption growth in both countries. Second, the tendency of lower income deciles to have higher consumption growth is substantially stronger in Peru than in the U.S. In the U.S., the average two-year-over-two-year growth of annual consumption in the bottom decile is 7.8 percentage points higher than that in the top decile, while the standard deviation of the consumption growth is 38.7 percent for the whole sample. In Peru, the year-over-year growth of quarterly consumption in the bottom decile is 30.2 percentage points higher than that in the top decile, while the standard deviation of the consumption growth is 45.3 percent for the whole sample. Both of these patterns suggest that liquidity constraints are the main driver of the stronger MPC heterogeneity in Peru than in the U.S.

Once we accept that liquidity constraints are the main cause for the stronger MPC heterogeneity over the income distribution in Peru, we can decompose the cross-country MPC gap into two parts:

(i) the gap caused by households being more affected by liquidity constraints in Peru than in the U.S. and (ii) the gap caused by factors unrelated to liquidity constraints, such as cross-country differences in preferences and interest rates. We can conduct this decomposition by identifying a top income group composed of households that are not only currently unconstrained but also highly unlikely to be constrained in the future (forwardly unconstrained households hereafter) in each country. The MPC gap between forwardly unconstrained households in Peru and those in the U.S. captures the gap caused by factors unrelated to liquidity constraints.

To delineate a top income group composed of forwardly unconstrained households, I exploit the fact that MPC should be homogeneous over the income within this group. I test whether MPC is homogeneous for the top $(10n)\%$ income groups for $n = 1, \cdots, 10$ by employing a test suggested by Davies (1977) and Davies (1987). This test shows that the top 20% or larger income groups in Peru reject the null hypothesis that MPC is homogeneous over the income, and the top 60% or larger income groups in the U.S. reject the null hypothesis.

Based on this result, I delineate a top income group composed of forwardly unconstrained households in each country by the top 10% of households in Peru and the top 50% of households in the U.S., which are the largest top $(10n)\%$ income groups in each country that fail to reject the null hypothesis of the test. Under this delineation, 56.0 percent of the cross-country MPC gap is attributable to households being more affected by liquidity constraints in Peru than in the U.S. This finding is a conservative estimate of the role of liquidity constraints in the MPC gap because the delineation is likely to overrate the size of a true forwardly unconstrained top income group, which can cause an overestimation of the MPC of forwardly unconstrained households in Peru.

There is a burgeoning literature examining how macroeconomic dynamics or policy effects are affected by the presence of liquidity-poor households and their consumption behavior. For example, Krueger, Mitman, and Perri (2016) show that in an environment where a sizable fraction of liquidity-poor households exist, aggregate consumption can drop far more severely during bad times largely due to their enhanced precautionary-saving behavior in the face of increased unemployment risk. Kaplan et al. (2018) show that in a heterogeneous agent New-Keynesian (HANK) model with a two-asset environment, monetary policy works through a different mechanism than a conventional representative agent New-Keynesian framework (RANK) because liquidity-constrained households do not intertemporally substitute consumption much in response to interest rate changes but instead respond sensitively to temporary income changes. McKay, Nakamura, and Steinsson (2016) show that the effect of forward guidance is much weaker in a HANK model than in a RANK model since households do not respond much to a news shock on the real interest rate because of their shortened effective planning horizon (due to the liquidity constraints) and precautionary-saving motives. Oh and Reis (2012) show that targeted transfers can be effective in mitigating recessions by reducing the wealth of marginal workers (thus incentivizing them to work) and by reallocating wealth from low-MPC to high-MPC households.

It is noteworthy that all these studies are based on quantitative models fitted to the U.S. economy. The findings of chapter 1 and chapter 2 suggest that all these recently discovered mechanisms, through which liquidity-poor households and their consumption behavior affect aggregate dynamics or policy effects, could play a significantly larger role in emerging economies than in developed economies. In this regard, the findings of chapter 1 and chapter 2 suggest a new direction for the macroeconomic modeling of emerging economies. At the heart of the workhorse models for emerging market business cycles, such as Neumeyer and Perri (2005), Aguiar and Gopinath (2007), and Garcia-Cicco, Pancrazi, and Uribe (2010), representative households can borrow frictionlessly in optimizing their consumption paths. There exist other types of emerging market models that have explicit borrowing limits, such as sudden stop models and sovereign default models.[1] In these models, however, borrowing constraints bind only infrequently because they aim at explaining macroeconomic dynamics during infrequent episodes such as financial crises or sovereign defaults. Instead, the findings of chapter 1 and chapter 2 call for a new macroeconomic model of emerging economies in which there is a substantial fraction of liquidity-poor households even in normal times, and their MPC is as large as the estimates from the data. Revisiting impor-

[1] Sudden stop models such as Mendoza (2010) and Bianchi (2011) impose collateral constraints on representative households' borrowing. Sovereign default models such as Arellano (2008) and Mendoza and Yue (2012) limit the access of any domestic agent to the international financial market during periods of sovereign default.

tant macroeconomic questions for emerging economies – such as their distinctive business cycle features, aggregate dynamics during crises, and effects of various policies – through the lens of such a new model would be an important future avenue for the international macroeconomics literature. In chapter 3, I construct such a new model and evaluate the business-cycle implication of the substantial presence of the liquidity-poor, high-MPC households in emerging economies.

The remainder of this chapter is organized as follows. In section 2.2, I explore theory-guided possible explanations for the stronger MPC heterogeneity over income deciles in Peru. Then, I disentangle them by using relevant data patterns. Based on the finding that liquidity constraints mainly drive the stronger MPC heterogeneity in Peru, in section 2.3, I evaluate the role of liquidity constraints in the cross-country MPC gap. Section 2.4 concludes this chapter.

2.2 The Main Driver of the Stronger MPC Heterogeneity in Peru

Why do we observe the differences between the MPC graph over the income deciles of Peruvian households and that of U.S. households in Figure 1.1? I begin an investigation to answer this question by attempting to determine the main driver of the stronger within-country MPC heterogeneity over the income deciles in Peru.

When we see Figure 1.1 through the lens of the standard incomplete-market precautionary-saving models such as the underlying model discussed in subsection 1.2.1, there are three possible explanations for the stronger MPC heterogeneity over the income distribution in Peru.

First, households in lower income deciles could exhibit higher MPC because they are more likely to be constrained. In the underlying model, households that receive negative transitory income shocks would want to bring their future resources to current consumption by running down their asset position.[2] As a result, they become more likely to be constrained. Since lower-income households are more likely to have received negative transitory income shocks and want to run down their asset position, they are more likely to be constrained than higher-income households.

[2]When the income process is composed of a persistent (not permanent) component and a transitory component, such as the sum of an AR(1) process and an i.i.d. process as given in Appendix A.4.6, negative income shocks to the persistent component can also induce households to run down their asset position.

The likelihood of being constrained could increase substantially faster in Peru than in the U.S. as households move from higher to lower income deciles, and this difference can explain the stronger MPC heterogeneity in Peru.

Second, households in lower income deciles could exhibit higher MPC in the absence of liquidity constraints if they tend to front-load consumption more heavily in their consumption path governed by the Euler equation. For example, consider a variant of the underlying model in which (i) liquidity constraints are removed, (ii) preference heterogeneity in patience β_i and intertemporal elasticity of substitution (IES) $1/\sigma_i$ is allowed, and (iii) $(\beta_i, 1/\sigma_i)$ can be correlated with the unpredictable component of income $y_{i,t}$. Moreover, assume that $\beta_i(1+r) < 1$ in the steady state, as in Aiyagari (1994). In such a model, household i's consumption is governed by the following Euler equation.

$$E_{t+j}\left[e^{\Delta Z'_{i,t+j+1}\varphi^{p}_{t+j+1}}\beta_i(1+r_{t+j})(C_{i,t+j+1}/C_{i,t+j})^{-\sigma_i}\right] = 1, \quad 0 \le j \le J_{i,t-1}.$$

In this model, households in lower income deciles could exhibit higher MPC if they tend to be less patient (lower β_i) or have higher IES (higher $1/\sigma_i$) because they front-load consumption more heavily, as Aguiar, Bils, and Boar (2019) note. If the tendency of lower-income households to front-load consumption more heavily is stronger in Peru than in the U.S., it could explain the stronger MPC heterogeneity in Peru.

Third, even when households' consumption path follows the Euler equation and the degree of front-loading is similar across the income deciles, households in lower income deciles could exhibit higher MPC by facing higher interest rates. When interest rates are different over the income deciles, the relative prices of consumption between today and tomorrow are also different, and these different relative prices generate different substitution effects and wealth effects. I eliminate the difference in the substitution effects by assuming that households' front-loading behavior is similar across the income deciles. The different wealth effects remain: when lower-income households face higher interest rates, they face relatively cheaper prices of future consumption, and thus, they consume more today. As a result, they exhibit higher MPC.[3] If the tendency of lower-income households to face higher interest rates is stronger in Peru than in the U.S., this stronger heterogeneity in interest rates could explain the stronger MPC heterogeneity in Peru.

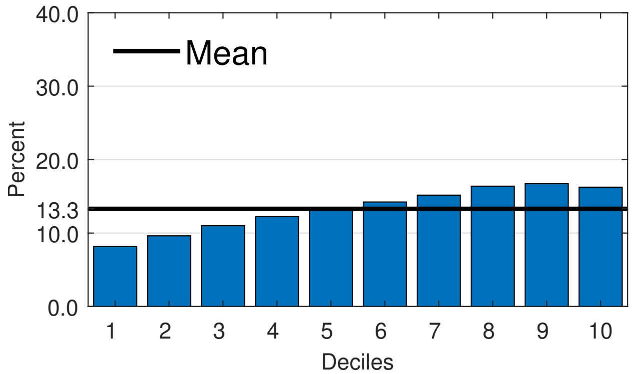
In the rest of this subsection, I try to disentangle these three theory-guided explanations using data. I begin with the last explanation with heterogeneous interest rates. This explanation makes sense only when the effective interest rates used by low-income households for their consumption-saving decision are borrowing interest rates.[4] To see if this is the case, I examine which fraction of households participate in borrowing activities in each of the income deciles in Peru.

In the sample years of 2015 and 2016, ENAHO includes survey questionnaires that make it possible to identify households that borrowed during the previous twelve months. Using these questionnaires, I identify type-1 observations as participants of borrowing activities if they fall into one of the two categories: (i) a household that has at least one member who reports in a member-level questionnaire that the member borrowed in the previous twelve months or (ii) a household that reports in a household-level questionnaire that it obtained loans or credit in the previous twelve months for the purpose of buying, extending or constructing housing. Figure 2.1a plots the share of type-1 observations identified as participants in borrowing activities in each of the income deciles from the 2015-2016 sample.[5] The income deciles are again constructed using the unpredictable (with observable characteristics) component of log income. Figure 2.1a shows that the share of households participating in borrowing activities is only 13.3 percent on average in

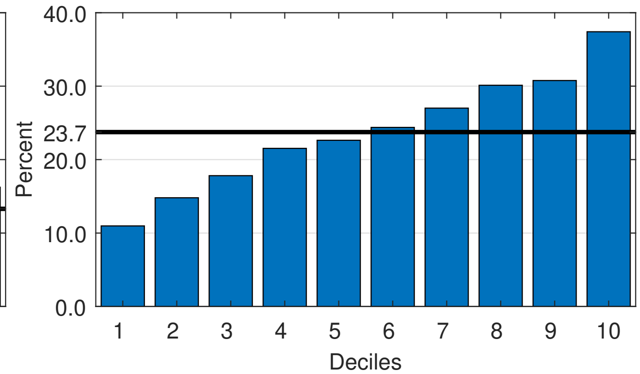
[3]For example, consider a textbook example in which households optimize their lifetime utility $\sum_{t=0}^{\infty} \beta^t C_t^{1-\sigma}/(1-\sigma)$ subject to sequential budget constraints $C_t + A_t = Y_t + (1+r)A_{t-1}$, the no-Ponzi game constraint, and a perfectly foresighted path of $\{Y_t\}$ under a parametric restriction, $\beta(1+r) = 1$. The optimized consumption path is flat (no front-loading), and the MPC out of a one-time transitory income shock is the annuity value of the shock, $r/(1+r)$. If patience β_i and interest rate r_i are allowed to be heterogeneous in such a way that i) $\beta_i(1+r_i) = 1$ always holds for each household i and ii) r_i tends to be higher in lower income deciles, the MPC in this model, $r_i/(1+r_i)$ is higher in lower income deciles even if their consumption path follows an Euler equation and the degree of front-loading is the same across all income deciles.

[4]Saving interest rates are unlikely to be higher for lower-income households. Interest rates on liquid assets such as checking accounts should be close to risk-free interest rates regardless of who holds them. Interest rates on illiquid assets can be substantially heterogeneous in such a way that rich households are more accessible to higher returns than poor households. See Fagereng, Guiso, Malacrino, and Pistaferri (2020) for recent empirical evidence on heterogeneous returns to wealth.

[5]Although I use only two years of the sample, the number of type-1 observations used in plotting Figure 2.1a is large. After implementing the sample selection applicable to type-1 observations discussed in subsection 1.3.3, the 2015 sample and the 2016 sample provide 21,675 and 23,552 observations of type-1, respectively.



(a) Baseline



(b) Including All Credit Card Holders

Figure 2.1: The Share of Peruvian Households Participating in Borrowing Activities in Each Income Decile from the 2015-2016 Sample

Notes: Figure 2.1a plots the share of type-1 observations identified as participants in borrowing activities in each of the income deciles from the 2015-2016 ENAHO sample. Figure 2.1b extends the definition of participants in borrowing activities by including credit card holders. In the x-axis of each figure, 1 is the bottom decile.

the Peruvian sample. Moreover, the share is even smaller in lower income deciles.

In Figure 2.1b, I add one more category of households when defining participants of borrowing activities: a household that has at least one member who holds a credit card. This definition may be excessively broad because some households might use credit cards only for transaction purposes rather than borrowing purposes. Even with this wide definition, the average share of households participating in borrowing activities is only 23.7 percent. Moreover, the tendency of lower-income households to be less likely to borrow than higher-income households is even stronger under this definition.[6]

Provided that the share of households participating in borrowing activities is as small as 13.3 percent - 23.7 percent in Peru and that the shares are even smaller in lower-income (higher-MPC) groups, it is unlikely that higher-MPC households face higher interest rates for their consumption-saving problem. Based on this observation, I eliminate the explanation with heterogeneous interest

[6] Demirguc-Kunt, Klapper, Singer, and Van Oudheusden (2015) and Demirguc-Kunt, Klapper, Singer, Ansar, and Hess (2018) compute similar statistics using their own surveys over a wide range of countries. They report that in Peru, the share of persons who '[b]orrowed from a financial institution (% age 15+)' is 11.2 percent, the share of persons who '[b]orrowed from a financial institution or used a credit card (% age 15+)' is 18.0 percent, and the share of persons who '[b]orrowed any money in the past year (% age 15+) ' including informal borrowings such as borrowing from family and friends is 32.2 percent in the 2014 survey. The shares are 14.7 percent, 19.1 percent, and 36.5 percent, respectively, in the 2017 survey.

rates.

The remaining two explanations, one with liquidity constraints and the other with front-loading behavior, are distinguishable by examining the consumption growth in the following period. Under the explanation with liquidity constraints, households in lower income deciles should exhibit higher consumption growth in the following period because when they become constrained, they fail to bring future resources to current consumption, and therefore, their consumption jumps in the following period. In equation (1.10), households constrained in period $t-K$ have higher values of $\sum_{j=0}^{K-1} \tilde{\mu}_{i,t-j-1}$ and thus tend to exhibit higher values of $\Delta^K c_{i,t}$. Moreover, for this explanation to be able to account for the stronger heterogeneity in Peru, the tendency of lower income deciles to exhibit higher consumption growth should be stronger in Peru.

Under the explanation with front-loading behavior, households in lower income deciles should exhibit lower consumption growth in the following period exactly because they front-load consumption more heavily than households in higher income deciles. In equation (1.10), when group G is composed of heavy front-loading households, the front-loading behavior manifests as $E(\sum_{j=0}^{K-1} \xi_{i,t-j}|G) < 0$[7], and thus, the group average $\Delta^K c_{i,t}$ is low. Moreover, for this explanation to be able to account for the stronger heterogeneity in Peru, the tendency of lower income deciles to exhibit lower consumption growth should be stronger in Peru.

To compare the following-period consumption growth among the income deciles of each country, I run the following regression using type-2 observations.

$$\Delta^K c_{i,t} = \alpha + \sum_{j=1}^{9} \delta_j I_{D_j}(i,t) + u_{i,t} \tag{2.1}$$

in which $I_{D_j}(i,t)$ is a dummy variable on whether a type-2 observation of household i observed in period t and $t-K$ belongs to the j-th income decile in period $t-K$. Parameter δ_j represents the difference in the average consumption growth between the j-th income decile and the top income decile. Standard errors are clustered within each household. Figure 2.2 plots the estimated values

[7]Term $\xi_{i,t-j}$ captures this front-loading behavior by including term $\frac{1}{\sigma_i} \log \beta_i$. See Appendix A.1 for details on which terms are included in $\xi_{i,t-j}$.

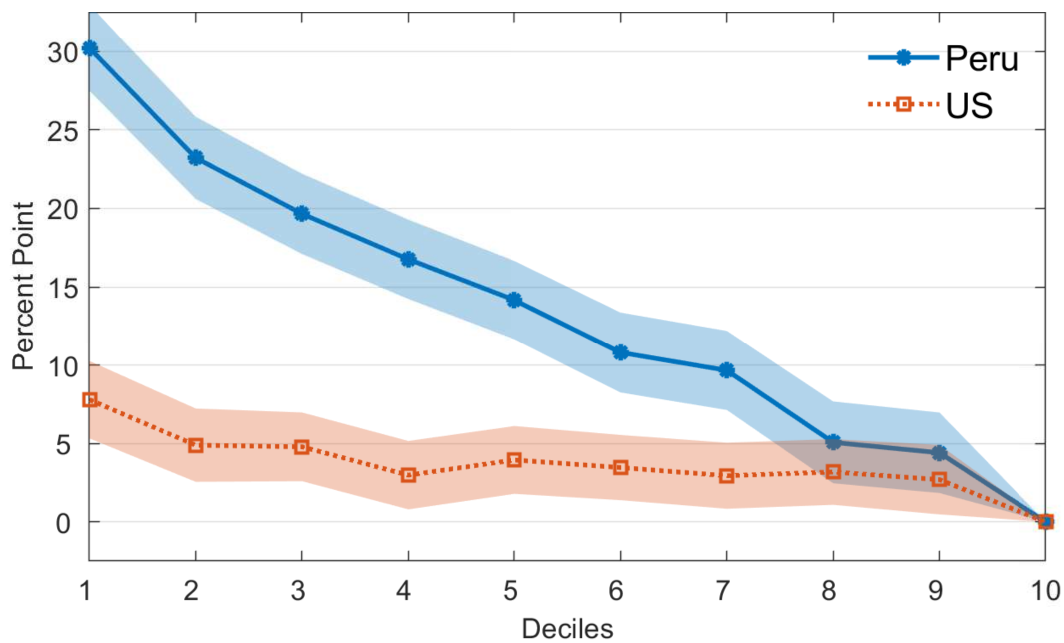


Figure 2.2: Group Average Consumption Growth Difference against the Top Income Decile

Notes: In the x-axis, 1 is the bottom decile. Shaded areas represent 95% confidence intervals.

of δ_j, $1 \leq j \leq 9$ in Peru and the U.S., respectively.[8]

Figure 2.2 exhibits two clear patterns. First, lower income deciles exhibit higher consumption growth in the following period in both countries.[9] Second, the tendency of lower income deciles to have higher consumption growth is substantially stronger in Peru than in the U.S. In the U.S., the average two-year-over-two-year growth of annual consumption of the bottom decile is 7.8 percentage points higher than that of the top decile, while the standard deviation of the consumption growth is 38.7 percent for the whole sample. In Peru, the year-over-year growth of quarterly consumption of the bottom decile is 30.2 percentage points higher than that of the top decile, while the standard deviation of the consumption growth is 45.3 percent for the whole sample.[10]

[8] Appendix B.1 reports the estimates and standard errors in a table for interested readers.

[9] In the context of the U.S. economy, this chapter is not the first to document the evidence of liquidity constraints using the negative relationship between consumption growth and lagged income. For example, Zeldes (1989) detects the presence of liquidity constraints for low-wealth households by regressing consumption growth on lagged income with other control variables.

[10] We observe the year-over-year growth of quarterly consumption in the Peruvian sample and two-year-over-two-year growth of annual consumption in the U.S. sample. Despite this difference in the growth units, the fact that the standard deviation of the observed consumption growth in the Peruvian sample (45.3 percent) is in the same ballpark as the standard deviation in the U.S. sample (38.7 percent) justifies the direct visual comparison of the two graphs in Figure 2.2. To illustrate this point, in Appendix B.2.12, I plot δ_j, $1 \leq j \leq 9$ in the unit of the standard deviations. The

These patterns support that liquidity constraints, rather than front-loading behavior, are the main driver of the stronger MPC heterogeneity over the income deciles in Peru.[11] [12]

2.3 The Role of Liquidity Constraints in the Cross-Country Mean MPC Gap

Once we accept that liquidity constraints are the main cause for the stronger MPC heterogeneity over the income distribution in Peru, we can decompose the cross-country mean MPC gap into two parts: (i) the gap caused by households being more affected by liquidity constraints in Peru than in the U.S. and (ii) the gap caused by factors unrelated to liquidity constraints, such as cross-country differences in preferences and interest rates. This decomposition can be conducted by identifying a top income group composed of forwardly unconstrained households in each country. The MPC gap between forwardly unconstrained households in Peru and those in the U.S. captures the gap caused by factors unrelated to liquidity constraints.

To delineate a top income group composed of forwardly unconstrained households, I exploit the fact that MPC should be homogeneous over the income within this group. I test whether MPC is homogeneous for the top $(10n)\%$ income groups for $n = 1, \cdots, 10$ by employing a statistical test suggested by Davies (1977) and Davies (1987) as follows. Let G be the top $x\%$ income

figure appears quite similar to Figure 2.2 and exhibits the same two main patterns discussed above.

[11] As discussed above, lower-income households are more likely to be constrained than higher-income households because the former are more likely to have received negative transitory income shocks and want to run down their asset position. If this is indeed the reason why we observe the two main patterns in Figure 2.2, we should observe the same patterns when we group observations by income growth $\Delta^K y_{i,t}$ instead of income level $y_{i,t}$ because the income growth also includes temporary income shock $\epsilon_{i,t}$, as seen in equation (1.9). In Appendix B.2.11, I verify that this is indeed the case. This robustness check can reduce the concern that the patterns in Figure 2.2 might be caused by some omitted factors correlated with both the income level and the consumption growth. For example, if poor households tend to experience higher inflation, the practice of deflating all nominal variables with the same CPI series can mechanically generate the pattern of lower-income households exhibiting higher consumption growth. However, this explanation cannot account for the fact that the same patterns emerge when observations are sorted by the income growth instead of the income level.

[12] Admittedly, my analyses in chapters 1 and 2 use income grouping instead of wealth or liquid-wealth grouping (which are more common grouping strategies in the literature) because ENAHO does not collect wealth information. However, it is also noteworthy that the income grouping I use in chapters 1 and 2 might have an advantage in detecting the effect of liquidity constraints compared to wealth or liquid-wealth grouping. In accordance with Aguiar et al. (2019)'s finding, I find that the consumption growth of hand-to-mouth households in Kaplan et al. (2014b)'s dataset is not significantly greater than that of non-hand-to-mouth households, indicating that the former might not be necessarily more constrained than the latter. In contrast, under the income grouping, we observe clear patterns in the same U.S. sample that lower income deciles exhibit higher consumption growth than higher income deciles. Appendix B.3 provides further details of the discussion.

group. For any $\omega \in [\underline{\omega}, \bar{\omega}] \subsetneq [0, 1]$, let $G_u(\omega)$ be the top $(\omega x)\%$ income group and $G_l(\omega)$ be $G_l(\omega) := G \backslash G_u(\omega)$. Let $z_G(\omega)$ be

$$z_G(\omega) := \frac{MPC_{G_l(\omega)} - MPC_{G_u(\omega)}}{s.e.\big(MPC_{G_l(\omega)} - MPC_{G_u(\omega)}\big)}$$

in which $s.e.(X)$ represents the standard error of statistic X. The test statistic for MPC homogeneity within group G, $z_G^{\sup}$, is defined as follows.

$$z_G^{\sup} := \sup_{\omega \in [\underline{\omega}, \bar{\omega}]} z_G(\omega).$$

The null hypothesis, '$H_0 : MPC_{G_l(\omega)} = MPC_{G_u(\omega)}, \forall \omega \in [\underline{\omega}, \bar{\omega}]$' is rejected in favor of the alternative hypothesis, '$H_1 : \exists \omega \in [\underline{\omega}, \bar{\omega}]$ such that $MPC_{G_l(\omega)} > MPC_{G_u(\omega)}$' when the value of $z_G^{\sup}$ is high enough.[13]

For the implementation of the test, three specific details need to be discussed. First, in estimating $z_G(\omega)$ for a given value of ω, we cannot assume that $MPC_{G_l(\omega)}$ and $MPC_{G_u(\omega)}$ are independent because observations for the same household at different times are correlated and can belong to different groups. Therefore, I estimate them jointly. Specifically, I estimate $\big(\kappa^\omega_{G_u}, \alpha^\omega_{G_u}, \psi^\omega_{G_u}, \kappa^\omega_{G_l}, \alpha^\omega_{G_l}, \psi^\omega_{G_l}\big)$ from the following moment conditions using the GMM method.

$$\begin{aligned} E\big[\{\kappa^\omega_{G_s} Y_{i,t-K} - C_{i,t-K}\} \cdot I^\omega_{G_s}(i,t) \big| (i,t) \in G\big] = 0, &\quad s = u, l \\ E\big[\{\Delta^K c_{i,t} - \alpha^\omega_{G_s} - \psi^\omega_{G_s} \Delta^K y_{i,t}\} \cdot I^\omega_{G_s}(i,t) \big| (i,t) \in G\big] = 0, &\quad s = u, l, \quad \text{and} \\ E\big[\{\Delta^K y_{i,t+K}(\Delta^K c_{i,t} - \alpha^\omega_{G_s} - \psi^\omega_{G_s} \Delta^K y_{i,t})\} \cdot I^\omega_{G_s}(i,t) \big| (i,t) \in G\big] = 0, &\quad s = u, l. \end{aligned} \tag{2.2}$$

in which $I^\omega_{G_s}(i,t)$ $(s = u, l)$ is a dummy variable indicating whether observation (i,t) belongs to $G_s(\omega)$ or not. Standard errors are clustered within each household.

Second, we need to set the boundary of $[\underline{\omega}, \bar{\omega}]$ and discretize it to compute $z_G^{\sup}$. I set $\underline{\omega} = 0.1$, $\bar{\omega} = 0.9$ and discretize it by the interval size of 0.01.

[13] Here, I restrict the alternative hypothesis to be one-sided instead of two-sided. This restriction can be supported by both theory and the empirical evidence presented in chapters 1 and 2.

Third, we need to set a rejection region. Davies (1977) provides a tight upper bound of significance probability ($P[\sup_{\omega\in[\underline{\omega},\bar{\omega}]} z_G(\omega) > c]$) under the null hypothesis, and Davies (1987) provides a way to approximate the upper bound with the data in use. Moreover, Davies (1987) shows that the p-value computed by the approximated upper bound performs well in the author's simulation example in terms of the rejection probability being close to the targeted significance level under the null hypothesis. Adopting Davies (1987)'s suggestion, I compute the p-value of the test as follows.

$$p = \Phi(-z_G^{\text{sup}}) + V \exp\big(-\frac{1}{2}(z_G^{\text{sup}})^2\big)/(8\pi)^{1/2} \tag{2.3}$$

in which Φ is the cumulative normal distribution function, and

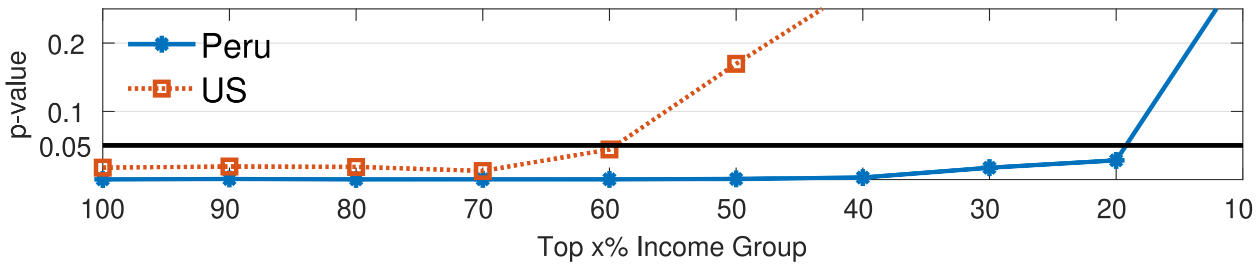
$$V = |z_G(\omega_1) - z_G(\underline{\omega})| + |z_G(\omega_2) - z_G(\omega_1)| + \cdots + |z_G(\bar{\omega}) - z_G(\omega_n)|$$

in which $\omega_1, \cdots, \omega_n$ are the discretized points within $[\underline{\omega}, \bar{\omega}]$. I reject the null hypothesis that MPC is homogeneous in group G if the p-value computed by equation (2.3) is smaller than 0.05.[14]

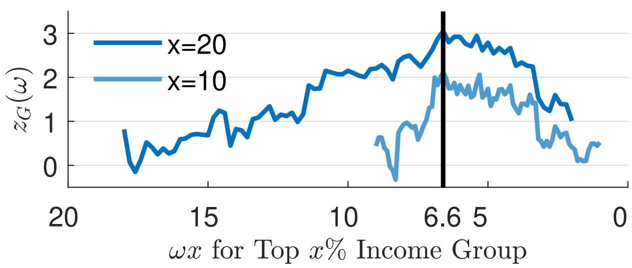
Figure 2.3a plots the p-values computed using equation (2.3) for the top $(10n)\%$ income groups, $n = 1, \cdots, 10$. This figure shows that in Peru, the top 10% income group fails to reject the null hypothesis of the MPC homogeneity test, while the top 20% or larger income groups reject it. In the U.S., the top 50% or smaller income groups fail to reject the null hypothesis, while the top 60% or larger income groups reject it. Based on this result, in my baseline decomposition, I delineate a top income group composed of forwardly unconstrained households in each country by the Peruvian top 10% and the U.S. top 50% income groups, which are the largest top $(10n)\%$ income groups in each country that fail to reject the null hypothesis.

It is worth noting, however, that the Peruvian top 10% and the U.S. top 50% income groups

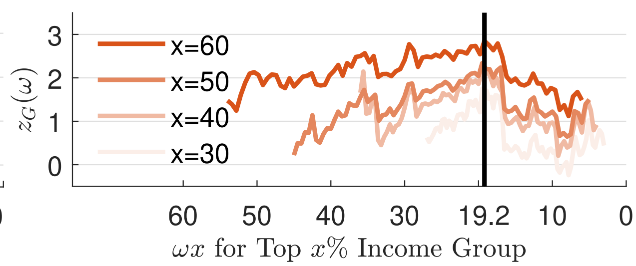
[14]Some econometric studies investigate similar problems with Davies (1977) and Davies (1987) in a specific econometric framework and draw an asymptotic distribution of the test statistic for the sup test. The most closely related setups to my econometric setup are those in Caner and Hansen (2004) and Andrews (1993). However, they require assumptions that do not fit my econometric setup. Caner and Hansen (2004) study an IV estimation method of a threshold model with endogenous regressors. Their method requires the threshold variable to be exogenous, but in my setup, the threshold variable $y_{i,t-K}$ is endogenous. Andrews (1993) studies tests for the parameter instability of the GMM estimators. The method is for a change-point model or, equivalently, a threshold model in which the threshold variable is time.



(a) p-value of the MPC Homogeneity Test for the Top $x\%$ Income Group



(b) $z_G(\omega)$, $\omega \in [0.1, 0.9]$ in Peru



(c) $z_G(\omega)$, $\omega \in [0.1, 0.9]$ in U.S.

Figure 2.3: MPC Homogeneity Test for Top Income Groups

Notes: Figure 2.3a plots the p-values of the MPC homogeneity test for the top $x\%$ income groups, $x = 10, 20, \cdots, 100$. Figure 2.3b and Figure 2.3c plot $z_G(\omega)$'s with varying values of $\omega \in [0.1, 0.9]$ for different top income groups in Peru and the U.S., respectively. The vertical black line indicates where $z_G(\omega)$ is at its maximum for the Peruvian top 20% income group in Figure 2.3b and for the U.S. top 60% income group in Figure 2.3c.

are likely to be strictly larger than the true largest MPC-homogeneous top income group. Figure 2.3b plots $z_G(\omega)$'s with various values of $\omega \in [0.1, 0.9]$ used in the MPC homogeneity test for the Peruvian top 20% income group, which is the smallest top $(10n)\%$ income group that rejects the null in Peru. In the test, $z_G(\omega)$ is maximized at the 6.6 percentile from the top, which is located within the top 10% income group. Moreover, Figure 2.3b plots $z_G(\omega)$'s used in the MPC homogeneity test for the Peruvian top 10% income group and shows that $z_G(\omega)$ is maximized around the 6.6 percentile from the top, again. These patterns suggest that the threshold for MPC homogeneity is located around the 6.6 percentile from the top, which is located within the top 10% income group, but the top 10% income group fails to reject the null hypothesis due to a lack of power.

Similarly, Figure 2.3c plots $z_G(\omega)$'s with various values of $\omega \in [0.1, 0.9]$ used in the MPC homogeneity test for the U.S. top 60% income group, which is the smallest top $(10n)\%$ income group that rejects the null in the U.S. In the test, $z_G(\omega)$ is maximized at the 19.2 percentile from the top, which is located within the top 50%, top 40%, and top 30% income groups. Moreover, in the test for these smaller top income groups (the top 50%, top 40%, and top 30%), $z_G(\omega)$ is maximized around the 19.2 percentile from the top, again. These patterns suggest that the threshold for the MPC homogeneity is located around the 19.2 percentile from the top, which is located within the top 50%, top 40%, and top 30% income groups, but these groups fail to reject the null hypothesis due to a lack of power.

Overrating the size of a forwardly unconstrained top income group can cause an overestimation of the MPC of forwardly unconstrained households in Peru and a consequent underestimation of the role of liquidity constraints in the cross-country mean MPC gap decomposition. In this sense, the baseline decomposition provides a conservative estimate for the role of liquidity constraints. To illustrate this point, I also conduct the mean MPC gap decomposition under an alternative delineation of forwardly unconstrained top income groups, the Peruvian top 5% and the U.S. top 15%. These top income groups are chosen to be above the income percentile cutoffs that maximize $z_G(\omega)$ in Figure 2.3b and Figure 2.3c, respectively.

Under each delineation of forwardly unconstrained top income groups, I decompose the cross-country mean MPC gap into two parts (the gap between the two countries' forwardly unconstrained households and the gap caused by households being more affected by liquidity constraints in Peru than in the U.S.) as follows.

Let $\mathcal{G} = \{G_1, G_2, \cdots, G_{n_{\mathcal{G}}}\}$ be a partition of the sample over the income distribution. For example, when I split the sample by the income deciles, $n_{\mathcal{G}} = 10$ and $G_1, \cdots, G_{10}$ represent the income deciles, $D_1, \cdots, D_{10}$. The mean MPC of the sample, MPC_{mean}, is computed by

$$MPC_{mean} = \sum_{G_j \in \mathcal{G}} \frac{w_{G_j}}{\sum_{G_{j'} \in \mathcal{G}} w_{G_{j'}}} MPC_{G_j} \tag{2.4}$$

in which w_{G_j} is the population weight of G_j and MPC_{G_j} is the MPC estimate of G_j. Let $\mathcal{U}$ be a subset of $\mathcal{G}$ that is composed of forwardly unconstrained groups. The MPC of forwardly unconstrained households, MPC_{uncon}, is computed by

$$MPC_{uncon} = \sum_{G_j \in \mathcal{U}} \frac{w_{G_j}}{\sum_{G_{j'} \in \mathcal{U}} w_{G_{j'}}} MPC_{G_j}. \tag{2.5}$$

Let MPC_{liq} be the difference between MPC_{mean} and MPC_{uncon}:

$$MPC_{liq} := MPC_{mean} - MPC_{uncon}. \tag{2.6}$$

Let MPC^{PR}_{mean}, MPC^{PR}_{uncon}, and MPC^{PR}_{liq} be the statistics computed using equations (2.4), (2.5), and (2.6), respectively, from the Peruvian sample, and MPC^{US}_{mean}, MPC^{US}_{uncon}, and MPC^{US}_{liq} be those from the U.S. sample. The cross-country mean MPC gap between Peru and the U.S., MPC^{gap}_{mean}, is computed by

$$MPC^{gap}_{mean} = MPC^{PR}_{mean} - MPC^{US}_{mean}. \tag{2.7}$$

The MPC gap between forwardly unconstrained households in Peru and those in the U.S., MPC^{gap}_{uncon}, is computed by

$$MPC^{gap}_{uncon} = MPC^{PR}_{uncon} - MPC^{US}_{uncon}. \tag{2.8}$$

Under the assumption that liquidity constraints are the sole source of the stronger MPC heterogeneity over the income distribution in Peru, the MPC gap caused by liquidity constraints, MPC^{gap}_{liq}, can be computed by

$$MPC^{gap}_{liq} = MPC^{gap}_{mean} - MPC^{gap}_{uncon} = MPC^{PR}_{liq} - MPC^{US}_{liq}. \tag{2.9}$$

In computing the standard errors of each country's MPC_{mean}, MPC_{uncon}, and MPC_{liq} in equations (2.4), (2.5), and (2.6), we cannot assume independence among MPC_{G_j}'s, $G_j \in \mathcal{G}$ because observations for the same household at different times are correlated and can belong to different groups. Therefore, I estimate them jointly using the GMM method in the same way that I jointly estimate $MPC_{G_u(\omega)}$ and $MPC_{G_l(\omega)}$ using moment conditions (2.2) for the MPC homogeneity test. Standard errors are clustered within each household in the GMM estimation. In computing the standard errors of MPC^{gap}_{mean}, MPC^{gap}_{uncon}, and MPC^{gap}_{liq} in equation (2.7), (2.8), and (2.9), I assume independence between the Peruvian sample and the U.S. sample.

In the baseline mean MPC gap decomposition, I partition each country's sample by the income deciles and delineate a forwardly unconstrained top income group by the Peruvian top 10% and the U.S. top 50%, as discussed above. Panel A of Table 2.1 reports the results. The gap between the mean MPC of Peru (63.2 percent) and that of the U.S.(8.9 percent) is 54.3 percentage points. The gap between the MPC of forwardly unconstrained households in Peru (29.9 percent) and that in the U.S.(6.0 percent) is 23.9 percentage points. As a result, 30.4 percentage points, which accounts for 56.0 percent of the mean MPC gap (54.3 percentage points), is attributable to Peruvian households being more affected by liquidity constraints than U.S. households.

Under the alternative delineation of forwardly unconstrained top income groups by the Peruvian top 5% and the U.S. top 15%, the mean MPC gap decomposition requires a finer partition than deciles. For the finer partition, I group observations by vigintiles of the income. To see whether the change in the partition itself affects the decomposition, in Panel B of Table 2.1, I conduct the decomposition under the baseline delineation of forwardly unconstrained top income groups (the Peruvian top 10%, the U.S. top 50%) and grouping by the income vigintiles. The numbers reported in Panel B are quite similar to those in Panel A, indicating that the change in the partition itself does not affect the decomposition in a meaningful way.

Panel C of Table 2.1 reports the decomposition results under the alternative delineation (the Peruvian top 5%, the U.S. top 15%) and grouping by the income vigintiles. The mean MPC gap in Panel C (53.8 percentage points) is similar to that in Panel A (54.3 percentage points). However, the MPC gap between forwardly unconstrained households in Peru and those in the U.S. in Panel C (13.3 percentage points) is substantially smaller than the gap in Panel A (23.9 percentage points). This is because the MPC of forwardly unconstrained Peruvian households in Panel C (17.2 percent) is substantially smaller than the MPC in Panel A (29.9 percent) by 12.7

Table 2.1: Decomposition of the Cross-Country Mean MPC Gap

A. Grouping by Income Deciles, Peru Top 10% and U.S. Top 50% as Forwardly Unconstrained Income Groups			
	MPC_{mean}	MPC_{uncon}	MPC_{liq}
Peru	0.632	0.299	0.333
	(0.028)	(0.086)	(0.081)
U.S.	0.089	0.060	0.029
	(0.014)	(0.014)	(0.014)
Gap	0.543	0.239	0.304
	(0.031)	(0.087)	(0.082)
B. Grouping by Income Vigintiles, Peru Top 10% and U.S. Top 50% as Forwardly Unconstrained Income Groups			
	MPC_{mean}	MPC_{uncon}	MPC_{liq}
Peru	0.627	0.319	0.308
	(0.028)	(0.083)	(0.079)
U.S.	0.089	0.060	0.029
	(0.015)	(0.014)	(0.014)
Gap	0.538	0.259	0.279
	(0.032)	(0.084)	(0.080)
C. Grouping by Income Vigintiles, Peru Top 5% and U.S. Top 15% as Forwardly Unconstrained Income Groups			
	MPC_{mean}	MPC_{uncon}	MPC_{liq}
Peru	0.627	0.172	0.455
	(0.028)	(0.118)	(0.114)
U.S.	0.089	0.039	0.051
	(0.015)	(0.018)	(0.020)
Gap	0.538	0.133	0.405
	(0.032)	(0.119)	(0.116)

percentage points, while the MPC of forwardly unconstrained U.S. households in Panel C (3.9 percent) is only 2.1 percentage points smaller than the MPC in Panel A (6.0 percent). As a result, 40.5 percentage points, which accounts for 75.2 percent of the mean MPC gap (53.8 percentage points), is attributable to Peruvian households being more affected by liquidity constraints than U.S. households. The results in Panel C verify that the MPC gap decomposition can underestimate the role of liquidity constraints when the size of the forwardly unconstrained top income group is overrated. In this sense, attributing 56.0 percent of the mean MPC gap to liquidity constraints in the baseline decomposition is a conservative estimation of its role.

2.4 Conclusion

This chapter explores possible explanations for the main findings of chapter 1, namely, i) the higher mean MPC and ii) the stronger MPC heterogeneity over income deciles in Peru compared to the U.S., and disentangle them by examining relevant patterns appearing in the micro data. Data patterns including participation rates in borrowing activities, consumption growth rates, and the MPCs of forwardly unconstrained top income groups delineated by an MPC homogeneity test suggest that liquidity constraints are important in accounting for both the higher mean MPC and the stronger MPC heterogeneity in Peru.

In a growing literature examining how micro heterogeneity matters for the macroeconomy, researchers have discovered novel mechanisms through which liquidity-poor households and their consumption behavior affect macroeconomic dynamics or policy effects in the context of developed economies. The results of chapter 1 and chapter 2 suggest that these mechanisms could play a significantly larger role in emerging economies. In this regard, these chapters also suggest that we need a new macroeconomic model of emerging economies in which a large fraction of households are affected by liquidity constraints not only during infrequent sudden-stop or sovereign-default episodes but also even during normal times, and their consumption responses are as strong as the empirical estimates of chapter 1. Examining the macroeconomic consequences of the liquidity-poor households' consumption behavior through the lens of such a new model would be an important topic for future research in the field of international macroeconomics. In chapter 3, I construct such a model and study the macroeconomic implication of the MPC gap between Peru and the U.S. on their business cycle differences.

Chapter 3: Emerging Market Business Cycles with Heterogeneous Agents

3.1 Introduction

One of the most salient patterns of emerging market business cycles is the phenomenon of 'excess consumption volatility': consumption is more volatile than output in emerging economies, while it is not in developed economies. An extensive literature is devoted to explaining excess consumption volatility, and the dominant modeling framework is representative-agent small open economy models. At the heart of these models, representative households optimize according to the permanent income hypothesis (PIH) because they can frictionlessly borrow from the international financial market. More importantly, the widely accepted mechanisms for excess consumption volatility in the literature crucially depend on the PIH behavior of households. However, micro data suggest that the PIH is not a good description of the consumption behavior of households in emerging economies. Chapter 1 estimates the marginal propensity to consume (MPC) out of transitory income shocks by applying a standard estimation method devised by Blundell et al. (2008) to a Peruvian household survey and finds that the MPC estimates of Peru are substantially greater than those of the U.S. obtained by the same method. Given that the MPC out of transitory income shocks is close to zero under the PIH, this micro evidence suggests that the consumption behavior of households deviates significantly from the PIH in emerging economies.

Motivated by this observation, this chapter revisits the driving mechanisms of emerging market business cycles through the lens of a heterogeneous-agent small open economy model in which households' MPCs are as high as the empirical estimates from the Peruvian data. To the best of my knowledge, this is a first attempt to study emerging market business cycles using a heterogeneous-agent model. To achieve empirically realistic MPCs in the model, I introduce Kaplan et al. (2018)'s two-asset environment over different degrees of liquidity into the model and calibrate the parameters governing financial frictions for illiquid assets (which are incorporated as adjustment costs for these assets in the model) jointly with the time discount factor by targeting the empirical MPC estimates.[1] I then take this model to Peruvian macro data through Bayesian estimation to explain emerging market business cycles.

After the Bayesian estimation, the model successfully generates the stylized patterns of emerging market business cycles, including excess consumption volatility. To evaluate the role of high-MPC households (or, more precisely, the role of the environment that makes households exhibit high MPCs) in emerging market business cycles, I run a counterfactual experiment in which Peruvian households are replaced with those exhibiting U.S. MPCs, which are substantially lower than Peruvian MPCs. Specifically, I recalibrate a subset of parameters including the time discount factor and the parameters governing financial frictions for illiquid assets by targeting the U.S. MPCs. After the recalibration, I find that aggregate consumption volatility declines by 26%, and as a consequence, the phenomenon of excess consumption volatility disappears. This result suggests that high-MPC households play an important role in generating excess consumption volatility.

To examine the mechanisms through which high-MPC households contribute to the high consumption volatility of emerging economies, I conduct three decomposition exercises: variance decomposition, variance change decomposition, and consumption response decomposition. I begin by decomposing the variances into the components generated by each aggregate shock in the baseline Peruvian economy. This variance decomposition shows that consumption variations are mostly driven by two aggregate shocks: i) stationary productivity shocks, which are the usual technology shocks in real business cycle models, and ii) illiquidity shocks, which change the degree of illiquidity of illiquid assets by shifting their adjustment costs.[2]

Once I implement the same variance decomposition for the counterfactual economy in which

[1] I use a two-asset model because it can successfully target both the high MPCs and the correct amount of aggregate wealth: households can exhibit high MPCs by being liquidity poor while they hold a large amount of illiquid assets. In a one-asset model, on the other hand, households have to hold a small amount of assets to yield high MPCs. This leads to an insufficient amount of aggregate capital, which is problematic for a business cycle analysis.

[2] As we shall see later, Bayesian estimation assigns a sizable explanatory power for consumption variations to illiquidity shocks because of their crucial role in explaining a low correlation between consumption growth and investment growth, which is commonly observed in Peru and other emerging economies.

households are replaced with those exhibiting U.S. MPCs, I can decompose the variance changes between the baseline economy and the counterfactual economy into the changes generated by each shock. This variance change decomposition shows that consumption volatility substantially decreases in the counterfactual economy because both stationary productivity shocks and illiquidity shocks generate significantly less consumption variation.

Ultimately, consumption is determined by households after they observe the variations in variables that are relevant for their optimization, including prices and the degree of illiquidity. I name such variables ‘drivers’. To see why stationary productivity shocks and illiquidity shocks generate substantially less consumption variation in the counterfactual economy, I decompose households’ total consumption response with respect to these shocks into the consumption responses to each driver.

In response to a stationary productivity shock, I find that households’ total consumption response is mostly driven by two drivers in the baseline economy: labor income per idiosyncratic labor productivity and illiquid asset returns. In the counterfactual economy, the total consumption response is substantially weaker because the responses to both drivers are substantially weaker. Importantly, the responses to both drivers are weaker in the counterfactual economy despite the fact that the equilibrium paths of the two drivers after the shock are similar in the two economies. These observations reveal the first main channel through which high-MPC households contribute to aggregate consumption volatility: the consumption of high-MPC households in emerging economies responds to individual resource fluctuations (mainly generated by the two drivers) far more strongly than that of the counterfactual households exhibiting U.S. MPCs.

In response to an illiquidity shock, households’ total consumption response is mostly driven by the direct effect of the shock rather than by indirect effects through other drivers in the baseline economy. The direct effect changes households’ consumption as follows. In my model, households allocate the vast majority of their savings to illiquid assets because liquid asset returns are too low compared to illiquid asset returns.[3] Because households face large financial frictions in

[3]The liquid and illiquid asset returns on the balanced growth path are calibrated to match the long-run average values of deposit rates and lending rates in the data. On the balanced growth path, the aggregate amount of illiquid

trading illiquid assets in the baseline economy, it is expensive for them to cash out their illiquid assets when they need to do so by facing bad idiosyncratic income shocks. When an illiquidity shock hits the economy and the degree of illiquidity increases, it becomes more expensive for households to cash out their illiquid assets. In response to this shock, both households facing bad idiosyncratic income shocks and those facing good idiosyncratic income shocks reduce their consumption substantially. For households who face bad idiosyncratic income shocks at the moment of the illiquidity shock, they need to cash out their illiquid assets to smooth their consumption, but it is more difficult to do so because their assets are now more illiquid. As a consequence, they fail to smooth consumption more significantly, and their consumption plunges. For households who face good idiosyncratic income shocks at the moment of the illiquidity shock, they recognize that it will be more expensive to cash out their illiquid assets for a while. Therefore, they prepare themselves for situations in which bad idiosyncratic income shocks are realized in a near future by reducing consumption and accumulating more buffer stocks. In the counterfactual economy, this direct effect is substantially weaker because households face much weaker financial frictions in the first place. Therefore, even if the degree of illiquidity increases, it distorts households' consumption-saving decisions far more mildly in the counterfactual economy. These observations reveal the second main channel through which high-MPC households contribute to aggregate consumption volatility: their consumption plunges when assets become more illiquid because some of them experience aggravated consumption smoothing failure and others come to have an enhanced precautionary-saving motive.

There are existing theories for the excess consumption volatility of emerging economies based on representative-agent small open economy models. I find that the driving mechanisms of excess consumption volatility in these conventional theories do not play an important role in my model. The key reason is that these conventional mechanisms require the PIH behavior by households, while the high-MPC households in my model significantly deviate from it.

The first well-accepted theory in the literature is the one developed by Aguiar and Gopinath

assets is 51 times greater than that of liquid assets.

(2007). The main mechanism of this theory operates through households' strong consumption response to a trend shock (or, equivalently, a shock to the growth of technology) as follows. When a positive trend shock hits the economy, output not only increases today but also grows substantially in the future. Representative households who follow the PIH increase their current consumption substantially more than the current increase in output because their decisions reflect the large increase in their permanent income due to the future income growth. Similarly, when a negative trend shock hits the economy, households decrease their current consumption substantially more than the current decrease in output because they recognize the large decrease in their permanent income due to the negative future income growth. This mechanism enables representative-agent models to generate excess consumption volatility.

In my model, the future output growth in response to positive trend shocks enters into households' budget constraints through two channels. First, the future growth of aggregate labor income enters into households' budget constraints as the future growth of labor income per idiosyncratic labor productivity. Second, the future growth of aggregate capital income is reflected in the asset price of illiquid assets and thus enters into households' budget constraints as a jump in illiquid asset returns on impact. Both channels make households' idiosyncratic income profiles either more increasing or less decreasing, and by this positive wealth effect, households would want to consume more. However, there is a strong counteracting force in my model. The first of these two channels also increases future idiosyncratic income risk (as labor income per idiosyncratic labor productivity grows in the future), and households' precautionary-saving motive becomes stronger. In particular, because households allocate the vast majority of their savings to illiquid assets and it is expensive to cash out their illiquid assets when they need to do so by facing bad idiosyncratic income shocks, the amount of additional precautionary saving in response to the increased idiosyncratic risk is large. This enhanced precautionary-saving motive offsets most of the positive wealth effect, and as a result, the consumption response is substantially subdued. When negative trend shocks hit the economy, the mechanism operates in the opposite way. The shocks make households' idiosyncratic income profiles either less increasing or more decreasing and generate a negative wealth effect. However, a weakened precautionary-saving motive offsets most of this negative wealth effect. As a result, the consumption decrease in response to negative trend shocks is substantially dampened.

The second well-accepted theory in the literature is the one developed by Neumeyer and Perri (2005). The main mechanism of this theory operates through households' intertemporal substitution of consumption in response to interest rate variations. Emerging economies face volatile interest rate fluctuations, induced either by domestic economic conditions or purely external factors. These interest rate fluctuations change the relative prices of consumption between different time periods. When representative households who follow the PIH face these interest rate fluctuations, they intertemporally substitute their consumption. This intertemporal substitution can generate large consumption variations without any significant variations in output. Representative-agent models can explain excess consumption volatility by using this mechanism.

In my model, households cannot incorporate this mechanism well for two reasons. First, unlike representative households whose consumption is solely determined by their lifetime wealth and the degree of intertemporal substitution, the consumption-saving behavior of households in my model is also substantially affected by the precautionary-saving motive. Second, the fact that households in my model allocate most of their savings to illiquid assets makes it even more difficult for them to shift resources across time.

This chapter is closely related to two strands of literature. The first is a recently growing literature devoted to understanding how microlevel household behavior shapes macroeconomic dynamics or the transmission mechanisms of economic policies. Well-known works in this literature include Kaplan et al. (2018), Auclert (2019), Krueger et al. (2016), McKay et al. (2016), Auclert et al. (2018), Bayer, Luetticke, Pham-Dao, and Tjaden (2019), and Oh and Reis (2012), among many others. Many studies in this literature focus on the fact that even in advanced economies such as the U.S., a sizable fraction of households exhibit MPCs that are significantly higher than the MPCs predicted by the PIH. They examine how the model prediction changes once this fact is realistically incorporated into the model. This chapter contributes to this literature by exploiting a different margin: the MPCs of emerging economies are substantially greater than those of developed economies. It finds that once this margin is incorporated, microlevel household behavior matters for aggregate dynamics to the extent that it can actually explain one of the most salient patterns of emerging market business cycles, namely excess consumption volatility.

The second literature is the one devoted to explaining the stylized patterns of emerging market business cycles using macroeconomic models. Well-known works in this literature include Neumeyer and Perri (2005), Aguiar and Gopinath (2007), Uribe and Yue (2006), Garcia-Cicco et al. (2010), Chang and Fernández (2013), and Fernandez-Villaverde, Guerron-Quintana, Rubio-Ramirez, and Uribe (2011), among many others. All these studies are based on representative-agent models. This chapter contributes to this literature by bringing new intuitions and tools regarding how household heterogeneity and microlevel behavior affect aggregate dynamics from the first related literature, applying them in the context of emerging market business cycles, and deriving new explanations.

In addition to these two most closely related strands of literature, this chapter is also related to multiple other lines of research. In terms of methodology, this chapter has a commonality with Bayer, Born, and Luetticke (2020) and Auclert et al. (2020) in that Bayesian methods are applied to estimate a heterogeneous-agent model. Bayesian estimation requires a model to be solved a large number of times. It only recently became possible to solve heterogeneous-agent models fast enough to conduct Bayesian estimation thanks to the development of new computational methods. The main contributors to this recent computational development include Auclert et al. (2019), Boppart, Krusell, and Mitman (2018), Ahn, Kaplan, Moll, Winberry, and Wolf (2018), Bayer and Luetticke (2020), Winberry (2018), and Reiter (2009). Among the new methods, I use the one developed by Auclert et al. (2019).

This chapter is also related to studies that incorporate household heterogeneity into an open economy model. In this line of research, the most closely related to my work is Guntin, Ottonello, and Perez (2020). Guntin et al. (2020) compute the elasticity of group-average consumption to group-average income for each of income deciles during crises characterized by a large consumption decline using micro data and use the empirical results to identify the driving mechanism of the crises in a heterogeneous-agent small open economy model. There are also papers that study monetary phenomena through the lens of a heterogeneous-agent small open economy model with nominal frictions. De Ferra, Mitman, and Romei (2020) study how exchange rate fluctuations induced by a large current-account reversal affect the economy through the revaluation of households' foreign-currency-denominated debt. Sunel (2018) examines the welfare implication of a large and gradual disinflation that emerging economies experienced over the past two decades.[4]

The remainder of this chapter is organized as follows. Section 3.2 provides micro evidence on differences in MPCs between emerging and developed economies. After specifying the model in Section 3.3, I take the model to the data in section 3.4 through a two-step procedure that includes calibration and Bayesian estimation. In section 3.5, I run a counterfactual experiment in which households are replaced with those exhibiting U.S. MPCs. I then examine the underlying mechanisms through decomposition exercises in section 3.6. Section 3.7 examines the extent to which the mechanisms of conventional theories are dampened in my model and discusses the economic reasons. Section 3.8 concludes this chapter.

3.2 Micro Evidence

This chapter starts from the empirical finding of chapter 1 that MPCs out of transitory income shocks in emerging economies are substantially greater than those in developed economies. To obtain this finding, chapter 1 employs the method devised by Blundell et al. (2008), which is one of the widely accepted MPC estimation methods in the literature. This method imposes a theory-guided covariance structure on the joint dynamics of income and consumption and estimates the MPCs from this structure. Specifically, chapter 1 applies this method to a nationally representative Peruvian household survey, Encuesta Nacional de Hogares (ENAHO), which is one of the rare

[4]These studies and my chapter 3 incorporate household heterogeneity in asset positions and labor productivity as in Aiyagari (1994) and Kaplan et al. (2018). There are also studies that incorporate household heterogeneity in open economies by introducing a finite number of different types of households, such as Cugat (2019) and Iyer (2015).

emerging market micro datasets that satisfy the data requirements of the method.[5] Then, the Peruvian MPC estimates are compared with the U.S. MPC estimates obtained by the same method using the Panel Study of Income Dynamics (PSID).[6]

In this section, I make a few revisions to chapter 1's procedure that are necessary to use the MPC estimates in disciplining the model presented in this chapter. These revisions include i) a change in the consumption measure from nondurable consumption to total consumption (including both nondurable and durable consumption) to be consistent with the aggregate consumption measure, ii) a change in the sample periods necessary for the availability of some key durable expenses regarding the first change, and iii) a change in the income process specification to be consistent with the model specification in this chapter. I provide details of the MPC estimation procedure, the three revisions, and data processing in Appendix C.1.

After reflecting these changes, the final Peruvian sample used in this chapter comes from the 2011-2018 waves of ENAHO. Because ENAHO is conducted annually and provides one quarterly income and consumption per annual survey, we can obtain seven years of year-over-year growth of quarterly income and consumption from this sample. From this data structure, we can estimate quarterly MPCs of Peruvian households by applying Blundell et al. (2008)'s method. The blue solid line with circle markers in Figure 3.1 plots the MPC estimates over the labor income deciles of Peru.[7] The shaded area around the line represents the 95% confidence intervals.

The final U.S. sample used in this chapter comes from the 2005-2017 waves of the PSID. The PSID is conducted biannually during the sample period and provides one annual income and consumption per biannual survey. Therefore, the PSID sample gives six years of two-year-over-two-year growth of annual income and consumption. From this data structure, we can obtain

[5]Blundell et al. (2008)'s method requires household surveys to include both income and consumption. It also requires a panel structure such that households have to appear at least three consecutive times.

[6]Specifically, chapter 1 uses the replication dataset of Kaplan et al. (2014b), which the authors construct from the PSID to estimate Blundell et al. (2008)'s partial insurance parameter upon which MPC estimates in chapter 1 are also based. In this chapter, instead of reusing Kaplan et al. (2014b)'s dataset, I reconstruct the U.S. data from the PSID to incorporate the revisions discussed below.

[7]Admittedly, I do not use wealth grouping, which is a more common grouping strategy in the literature, because ENAHO does not include wealth data. Instead, I use labor income grouping because it can effectively detect the different degrees of liquidity constraint effects. (For example, Zeldes (1989) detects the presence of liquidity constraints by using lagged incomes as instruments.) See Appendix C.1.6 for details on how I construct the labor income deciles.

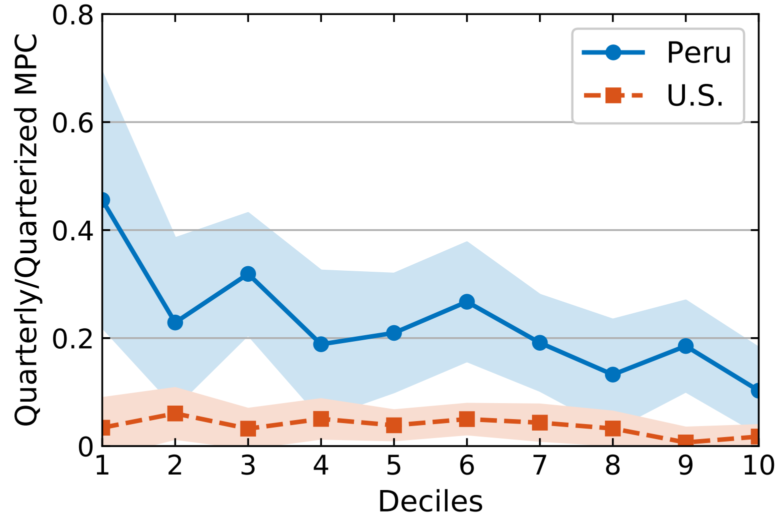


Figure 3.1: Quarterly/Quarterized MPC Estimates in Peru and U.S.

Notes: Figure 3.1 plots the quarterly MPC estimates of Peru and the quarterized annual MPC estimates of the U.S. according to Auclert (2019)'s model-free conversion formula: $1 - MPC_G^Q = (1 - MPC_G^A)^{0.25}$. Shaded areas represent 95% confidence intervals.

annual MPC estimates of U.S. households using Blundell et al. (2008)'s method. To compare the annual MPC estimates of the U.S. and the quarterly MPC estimates of Peru without resorting to a model, here I adopt the frequency-conversion formula that Auclert (2019) uses for the same purpose of comparing quarterly and annual MPC estimates:

$$1 - MPC_G^Q = (1 - MPC_G^A)^{0.25} \tag{3.1}$$

in which MPC_G^Q denotes the quarterly MPC and MPC_G^A denotes the annual MPC of group G.[8] The red dashed line with square markers in Figure 3.1 plots the quarterized U.S. MPC estimates according to this model-free frequency conversion (3.1) over the U.S. labor income deciles. The shaded area around the line represents the 95% confidence intervals.[9]

Figure 3.1 compares the quarterly Peruvian MPC estimates and the quarterized U.S. MPC

[8]Auclert (2019) derives this formula by assuming that the response of quarterly consumption in period $t + j$ to a shock in period t decreases exponentially in j, and the interest rate is close to zero. He argues that this formula is a good approximation in partial equilibrium Bewley models.

[9]When constructing the confidence intervals, the standard errors are also converted using equation (3.1) and the Delta method.

estimates. This figure reaffirms the empirical finding of chapter 1 that the MPCs of Peruvian labor income deciles are substantially higher than those of U.S. labor income deciles.

One important disadvantage in this comparison is that the model-free frequency conversion (3.1) cannot address the problem that the time frame applied to the Peruvian data is different from that applied to the U.S. data: Peruvian households are assumed to be subject to quarterly income processes and make quarterly consumption decisions, while U.S. households are assumed to be subject to annual income processes and make annual consumption decisions. This discrepancy can be directly taken into account once we have a model. I revisit this issue in section 3.5.

3.3 The Model

I construct a heterogeneous-agent small open economy model by combining i) the two-asset household heterogeneity over liquid and illiquid assets of Kaplan et al. (2018)[10] and ii) the standard emerging market, small open economy features of Garcia-Cicco et al. (2010).[11] One difficulty in combining these two structures is that conventional representative-agent small open economy models already have their own two-asset environment between international debt and capital in households' optimization. Since there is no obvious one-to-one mapping between the former two assets (liquid assets and illiquid assets) and the latter two assets (international debt and capital), letting households decide all of them requires more than two assets and thus is subject to the curse of dimensionality. I circumvent this problem by exploiting the following feature of conventional small open economy models: there are multiple ways to decentralize the economy (while maintaining the same set of equilibrium conditions), and one of them decentralizes it such that firms face the two-asset problem between international debt and capital, and households only deal with one asset, namely firm shares. I start from this decentralized version of the conventional small

[10]Note, however, that I do not incorporate the nominal rigidity of Kaplan et al. (2018)'s Heterogeneous-Agent New Keynesian (HANK) model because the model is intended to be as close as possible to the conventional real models of emerging economies except for household heterogeneity.

[11]The emerging market, small open economy features of Garcia-Cicco et al. (2010) include free access to the international financial market through which external debt is borrowed, the open goods market in which the gap between domestic output and demand is offset by net exports, and capital adjustment costs that are necessary for small open economy models to yield a realistic degree of investment fluctuations (because interest rates are directly affected by exogenous shocks and thus highly volatile in these models).

open economy model and incorporate the two-asset environment of Kaplan et al. (2018) into it by revising the firm shares into illiquid assets (by introducing adjustment costs in trading the shares) and additionally introducing liquid assets.

3.3.1 Households

A continuum of households live in this economy. Each household i is heterogeneous in its illiquid asset position $a_{i,t-1}$, liquid asset position $b_{i,t-1}$, and idiosyncratic labor productivity $e_{i,t}$ in each period t. The illiquid assets are the shares of firms that households hold, and the liquid assets are households' bank deposits. Households face the following tradeoff between illiquid assets and liquid assets: illiquid assets pay higher returns than liquid assets on the balanced growth path, but households have to pay adjustment costs when accumulating or running down illiquid assets (while liquid assets can be adjusted costlessly). Households cannot take short positions in both illiquid assets and liquid assets. In each period, household i solves the following optimization problem.

$$\max_{\{c_{i,t},b_{i,t},a_{i,t},v_{i,t}\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} \beta^t \frac{c_{i,t}^{1-\gamma}}{1-\gamma} \tag{3.2}$$

$$s.t.$$

$$c_{i,t} + b_{i,t} + v_{i,t} + \eta_t \chi_t(v_{i,t}, a_{i,t-1}) = w_t e_{i,t} \bar{l}_t + (1-\xi)(1+r_t^b) b_{i,t-1},$$

$$v_{i,t} = a_{i,t} - (1+r_t^a) a_{i,t-1}, \quad \text{and}$$

$$b_{i,t} \geq 0, \quad a_{i,t} \geq 0.$$

In the households' budget constraint, $(1 + r_t^a)$ is the gross return rate on illiquid assets, $(1 - \xi)(1+r_t^b)$ is the gross return rate on liquid assets, and $\eta_t \chi_t(v_{i,t}, a_{i,t-1})$ is the adjustment cost for the illiquid asset positions. Parameter ξ is strictly positive and $r^a = r^b$ on the balanced growth path.[12] The term $w_t e_{i,t} \bar{l}_t$ is the labor income of household i, in which w_t is the wage rate per efficiency unit

[12]As we shall see in subsection 3.3.3, $(1 + r_t^b)$ is banks' gross financing cost when they finance through intermediating household deposits. This financing cost consists of an intermediation cost $\xi(1 + r_t^b)$ that banks incur and a gross return on household deposits $(1 - \xi)(1 + r_t^b)$.

of labor and $\bar{l}_t$ is the labor supply. The labor supply is common to all households and determined by the labor union of the economy, which will be specified in the following subsection.[13]

The adjustment cost for illiquid assets, $\eta_t \chi_t(v_{i,t}, a_{i,t-1})$, is the product of two components: an aggregate shock to the degree of illiquidity η_t and the adjustment cost on the balanced growth path $\chi_t(v_{i,t}, a_{i,t-1})$. For the functional form of $\chi_t(v_{i,t}, a_{i,t-1})$, I closely follow Auclert et al. (2019)'s discrete-time version of Kaplan et al. (2018)'s model as follows.

$$\chi_t(v_{i,t}, a_{i,t-1}) = \chi_1 \left| \frac{v_{i,t}}{(1 + r_t^a)a_{i,t-1} + \chi_0 X_{t-1}} \right|^{\chi_2} \left((1 + r_t^a)a_{i,t-1} + \chi_0 X_{t-1} \right)$$

in which $\chi_0 > 0, \chi_1 > 0$, and $\chi_2 > 1$, and X_{t-1} is the stochastic trend of the economy.

Parameter χ_1 is the scaling factor for the adjustment cost, and it determines the overall importance of the adjustment cost term in households' optimization. As parameter χ_1 increases, it becomes more expensive to trade illiquid assets. Importantly, when parameter χ_1 is higher, households i) save more and ii) exhibit higher MPCs. For households facing bad idiosyncratic income shocks, they need to cash out their illiquid assets to smooth their consumption. However, it is more difficult to do so when χ_1 is higher, and therefore, they have to save more. Moreover,

[13] When individual households determine their labor supply under widely used preference specifications, the model exhibits counterfactual patterns in important dimensions. When the labor supply is determined by individual households under separable labor disutility, the aggregate labor supply declines substantially during booms because of the wealth effect. This phenomenon is common in macroeconomic models of emerging economies (including those with representative households) because they are designed to exhibit large consumption fluctuations, which also generate large fluctuations in the wealth effect. For this reason, macroeconomic models of emerging economies usually impose the preferences introduced by Greenwood, Hercowitz, and Huffman (1988) (GHH preferences hereafter) instead of separable labor disutility because the wealth effect disappears under GHH preferences. In my model, however, when individual households determine their labor supply under GHH preferences, another counterfactual pattern emerges: the MPC estimates from the model become abnormally high compared to the estimates from micro data. This is because under GHH preferences, the per-period utility over consumption c and labor supply l is given by $\frac{(c-g(l))^{1-\gamma}}{1-\gamma}$, and thus households tend to smooth $(c - g(l))$ rather than c. As a consequence, consumption comoves too strongly with income.

Note that in the HANK literature, researchers also find that models exhibit counterfactual patterns when individual households determine their labor supply, although on different aspects than the counterfactual patterns that my model exhibits under the individual labor supply decisions. Some researchers prefer to circumvent this problem by introducing a labor union to which the labor supply decision is delegated. (See Auclert and Rognlie (2017) for a detailed discussion of this issue in the context of the HANK literature.) In the same spirit, I introduce a labor union to circumvent the problem caused by the individual labor supply decisions in my model. In particular, I write the objective function of the labor union such that the aggregate labor supply equation is identical to that in a typical representative-agent model with GHH preferences. See subsection 3.3.2 for details on the optimization problem of the labor union.

these households exhibit higher MPCs when χ_1 is higher because of the aggravated consumption smoothing failure they experience. For households facing good idiosyncratic income shocks, their precautionary-saving motive is stronger when χ_1 is higher because they recognize that it will be more expensive to cash out their illiquid assets when they need to do so by facing bad idiosyncratic income shocks in the future. Therefore, they prepare themselves for such cases by accumulating more buffer stocks. Moreover, these households exhibit higher MPCs when χ_1 is higher because of their enhanced precautionary-saving motive.

When parameter χ_2 is equal to one, the adjustment cost becomes proportional to the absolute amount of illiquid asset position adjustment. As χ_2 increases above one, the adjustment cost becomes less costly for rich households (who have higher values of $(1 + r_t^a)a_{i,t-1}$). Therefore, parameter χ_2 captures how less costly it is for wealthier households to adjust their illiquid asset positions. For this reason, parameter χ_2 is useful to make rich and poor households face different degrees of financial frictions and thus have different MPCs. Later, I calibrate χ_1 and χ_2 (jointly with β) to match the MPC estimates and aggregate wealth. I find that calibrating this small number of parameters can effectively match the ten MPC moments over the labor income deciles and the correct amount of aggregate wealth in the economy.

I assume that idiosyncratic labor productivity $\log e_{i,t}$ is composed of a persistent component that follows an $AR(1)$ process and a transitory component that follows an $I.I.D.$ process as follows.[14]

$$\log e_{i,t} = \log e_{1,i,t} + \log e_{2,i,t},$$

$$\log e_{1,i,t} = \rho_{e_1} \log e_{1,i,t-1} + \epsilon_{1,i,t}, \quad \epsilon_{1,i,t} \sim N(0, \sigma_{\epsilon_1}^2),$$

$$\log e_{2,i,t} = \epsilon_{2,i,t}, \quad \epsilon_{2,i,t} \sim N(0, \sigma_{\epsilon_2}^2).$$

[14]The labor productivity process specification in the model is consistent with the income process specification imposed in the MPC estimation. When we generate individual households' log labor income $\log w_t e_{i,t} \bar{l}_t$ from the model and control for the time fixed effect as in the empirical MPC estimation, we obtain $\log e_{i,t}$ as the residual. Therefore, $\log e_{i,t}$ is the model counterpart of the residual of log income, $y_{i,t}$, in the empirical MPC estimation. As seen in Appendix C.1.1, the specification of the $\log e_{i,t}$-process in the model is exactly equal to the specification of the $y_{i,t}$-process in the MPC estimation.

Let $\Psi_t(e_1, e_2, b_-, a_-)$ denote the economy's cumulative distribution function of (e_1, e_2, b_-, a_-) in period t:

$$\Psi_t(e_1, e_2, b_-, a_-) := P(e_{1,t} \le e_1,\ e_{2,t} \le e_2,\ b_{t-1} \le b_-,\ a_{t-1} \le a_-).$$

Moreover, let $c_t(e_1, e_2, b_-, a_-)$, $b_t(e_1, e_2, b_-, a_-)$, and $a_t(e_1, e_2, b_-, a_-)$ denote the policy functions of households in period t.[15] The law of motion for the distribution can be described as follows.

$$\begin{aligned}\Psi_{t+1}(e_1', e_2', b, a) = \int_{e_1,e_2,b_-,a_-} & P(e_{1,t+1} \le e_1' | e_{1,t} = e_1) P(e_{2,t+1} \le e_2') \\ & I_{\{b_t(e_1,e_2,b_-,a_-)\le b,\ a_t(e_1,e_2,b_-,a_-)\le a\}}(e_1, e_2, b_-, a_-)\ d\Psi_t\end{aligned} \tag{3.3}$$

in which $I_{\{X\}}(x)$ is an indicator function (*i.e.*, $I_{\{X\}}(x) = 1$ if $x \in X$, 0 otherwise).

Let C_t, B_t, A_t, and χ_t^{agg} be the aggregate quantities that sum up the corresponding individual variables as follows.

$$\begin{aligned} C_t &= \int_{e_1,e_2,b_-,a_-} c_t(e_1, e_2, b_-, a_-)\ d\Psi_t, \\ B_t &= \int_{e_1,e_2,b_-,a_-} b_t(e_1, e_2, b_-, a_-)\ d\Psi_t, \\ A_t &= \int_{e_1,e_2,b_-,a_-} a_t(e_1, e_2, b_-, a_-)\ d\Psi_t, \quad \text{and} \\ \chi_t^{agg} &= \int_{e_1,e_2,b_-,a_-} \eta_t \chi_t(a_t(e_1, e_2, b_-, a_-) - (1 + r_t^a)a_-, a_-)\ d\Psi_t. \end{aligned} \tag{3.4}$$

By aggregating the individual households' budget constraints, we can obtain

$$C_t + B_t + A_t + \chi_t^{agg} = w_t \bar{e} \bar{l}_t + (1 - \xi)(1 + r_t^b)B_{t-1} + (1 + r_t^a)A_{t-1} \tag{3.5}$$

[15] I attach the time subscript to the policy functions because they depend on the state vector $\mathcal{S}_t$, which includes the distribution function $\Psi_t(e_1, e_2, b_-, a_-)$, the stochastic trend X_{t-1}, other predetermined variables and exogenous variables in the economy. I specify which objects constitute the state vector $\mathcal{S}_t$ in footnote 18 after I complete the model specification. Using the state vector $\mathcal{S}_t$, one can alternatively denote the policy functions as time-invariant functions $c(e_1, e_2, b_-, a_-; \mathcal{S}_t)$, $b(e_1, e_2, b_-, a_-; \mathcal{S}_t)$, and $a(e_1, e_2, b_-, a_-; \mathcal{S}_t)$.

in which $\bar{e} := E[e_{i,t}]$ is the cross-sectional average of idiosyncratic labor productivity.

3.3.2 Labor Union

The labor supply decision is made collectively by the labor union. The labor union linearly weights the cross-sectional average of labor income $w_t \bar{e} \bar{l}_t$ and labor disutility $X_{t-1} \frac{1}{1+\omega} \bar{l}_t^{1+\omega}$ in making the decision as follows.[16]

$$\max_{\bar{l}_t} \; w_t \bar{e} \bar{l}_t - \kappa \left(X_{t-1} \frac{1}{1+\omega} \bar{l}_t^{1+\omega} \right)$$

in which $\kappa > 0$. As a result of the labor union's optimization, the labor supply is determined by the following equation.

$$w_t \bar{e}^{1+\omega} = \kappa X_{t-1} (\bar{e} \bar{l}_t)^{\omega}. \tag{3.6}$$

Note that this aggregate labor supply equation is equal to that in conventional representative-agent small open economy models with GHH preferences. In this sense, my model does not deviate from the conventional models in the dimension of the aggregate labor supply.

3.3.3 Domestic Banks

There are an infinite number of representative and competitive domestic banks that finance funds either by intermediating household deposits or by borrowing from the international financial market and then lend the funds to firms. As introduced above, B_t is the aggregate amount of household deposits. Let D_t be the banks' debt from the international financial market and F_t be the amount of funds that the banks lend to firms. By construction, we have

$$F_t = B_t + D_t.$$

[16] In a model with stochastic growth, it is a common practice that labor disutility is augmented with stochastic growth X_{t-1}. As explained in Uribe and Schmitt-Grohé (2017), this practice technically enables the quantity variables of the model to grow along the balanced growth path while labor supply does not in the long run. The augmentation of X_{t-1} can be economically interpreted as an advancement of home-production technology, such as the popularization of dishwashers and microwave ovens.

$(1+r_t^b)$ is banks' gross financing cost when they finance through intermediating household deposits B_{t-1}. This financing cost consists of an intermediation cost $\xi(1+r_t^b)$ that banks incur and a gross return on household deposits $(1-\xi)(1+r_t^b)$. The banks can frictionlessly adjust their sources of financing, and therefore, the financing cost is equalized between the two sources. In other words, we have

$$1+r_t^b = 1+r_{t-1}, \quad t \geq 0 \tag{3.7}$$

in which r_{t-1} is the interest rate on the international debt D_{t-1}. Because banks are competitive and there is no additional cost in lending funds to firms, banks lend funds F_t to firms at interest rates r_t.

3.3.4 Firms

There are an infinite number of representative and competitive firms that produce outputs Y_t using capital K_{t-1} and labor L_t, make investment I_t to accumulate capital, and borrow funds F_t from domestic banks. Moreover, they facilitate trade in their own shares (which are illiquid assets from the perspective of households) and earn facilitation fees χ_t^{agg}.[17] Specifically, they solve the following optimization problem.

$$\max_{\{K_t,F_t,L_t,Y_t,I_t,\Pi_t\}_{t=0}^{\infty}} E_0 \sum_{t=0}^{\infty} Q_{o,t}\Pi_t \tag{3.8}$$

$$s.t.$$

$$\Pi_t = Y_t - w_t L_t - I_t - \Phi(K_t, K_{t-1}) + F_t - (1+r_{t-1})F_{t-1} + \chi_t^{agg},$$

$$Y_t = z_t K_{t-1}^{\alpha}(X_t L_t)^{1-\alpha},$$

$$\nu_t I_t = K_t - (1-\delta)K_{t-1},$$

[17] This is one way to return χ_t^{agg} to households. Alternatively, one could assume that the trade in firms' shares is facilitated by banks, illiquid assets are composed of banks' shares and firms' shares, and households can frictionlessly and instantaneously adjust the proportion of the two shares within the illiquid asset portfolio. This alternative specification yields the same equilibrium conditions.

$$\nu_t \Phi(K_t, K_{t-1}) = \frac{\phi}{2}\left(\frac{K_t}{K_{t-1}} - g^*\right)^2 K_{t-1},$$

$$Q_{0,t} = \begin{cases} 1 & \text{if} \quad t = 0, \\ \frac{1}{\prod_{s=1}^{t}(1+r_s^a)} & \text{otherwise,} \end{cases} \qquad \text{and}$$

$$\lim_{j \to \infty} \frac{F_{t+j}}{\prod_{s=1}^{j}(1 + r_{t+s}^a)} \leq 0$$

in which Π_t is the per-period profit, $\Phi(K_t, K_{t-1})$ is an adjustment cost for the accumulation of capital, z_t is the stationary component of firms' productivity, and X_t is the nonstationary component (or stochastic trend) of firms' productivity. The variable ν_t is an aggregate shock to capital accumulation: when ν_t is higher, firms need to spend a smaller amount of resources as investment and capital adjustment costs to achieve the same amount of capital K_t given the same amount of previous capital K_{t-1}. This shock is often called an investment shock in the literature, and Justiniano, Primiceri, and Tambalotti (2010) study its role in U.S. business cycles. Firms discount profit flows using return rates on illiquid assets. As we shall see in the following subsection, this objective function is the total value of the firms because illiquid assets are the shares of the firms that households hold.

3.3.5 Illiquid Asset Return and Price

Households' illiquid assets are the shares of firms they hold. Let $s_{i,t}$ be the share that individual household i holds when the total shares are normalized to 1. Let q_t be the price of the illiquid assets after the current profits are distributed as dividends. Since total shares are normalized to 1, q_t also represents the total value of the firms after distributing current profits. By construction, we have the following equations.

$$a_{i,t-1} = q_{t-1} s_{i,t-1}, \quad \text{and}$$

$$(1 + r_t^a) a_{i,t-1} = \Pi_t s_{i,t-1} + q_t s_{i,t-1}.$$

From these two equations, we can obtain

$$1 + r_t^a = \frac{\Pi_t + q_t}{q_{t-1}}, \quad t \geq 0. \tag{3.9}$$

By solving equation (3.9) forward and taking an expectation, we can obtain

$$q_t = E_t \sum_{j=1}^{\infty} \frac{\Pi_{t+j}}{\prod_{s=1}^{j}(1 + r_{t+s}^a)}.$$

Therefore, the objective function of the firms' optimization problem $E_0 \sum_{t=0}^{\infty} Q_{0,t}\Pi_t$ is equal to $\Pi_0 + q_0$. In other words, firms maximize their total value before distributing current profits. This explains why firms discount profit flows with illiquid asset returns in their optimization.

It is worth noting how $\{r_t^a\}_{t=0}^{\infty}$ are determined in equilibrium. The illiquid asset returns from period 1 onward, $\{r_t^a\}_{t=1}^{\infty}$, are subject to the following optimimality condition for firms with respect to determining F_t.

$$E_t \left[\frac{1 + r_t}{1 + r_{t+1}^a} \right] = 1, \quad t \geq 0. \tag{3.10}$$

When we consider the impulse responses after an MIT shock (*i.e.*, without aggregate uncertainty), this equation becomes $r_{t+1}^a = r_t, \ t \geq 0$. On the other hand, the illiquid asset return in period 0, r_0^a, is not determined by equation (3.10). Instead, r_0^a is solely determined by Π_0, q_0, and q_{-1} through equation (3.9).

3.3.6 Interest Rates in the International Financial Market

The interest rates in the international financial market, r_t, are specified in a standard way as follows.

$$r_t = r^* + \psi \left\{ \exp\left(\frac{\hat{D}_t / X_t - \tilde{D}^*}{\tilde{Y}^*} \right) - 1 \right\} - \theta_z (z_t - 1) - \theta_g \left(\frac{g_t}{g^*} - 1 \right) + \mu_t - 1 \tag{3.11}$$

in which $\psi > 0$, $\theta_z > 0$, and $\theta_g > 0$. r^* is the long-run average of the interest rate, and $\hat{D}_t$ is the cross-sectional average of firms' international debt. Individual firms regard $\hat{D}_t$ as exogenously given, but in equilibrium, individual firms' international debt D_t is equal to their cross-sectional average $\hat{D}_t$:

$$\hat{D}_t = D_t. \tag{3.12}$$

$\tilde{D}^*$ is the long-run average of $\hat{D}_t/X_t$, $\tilde{Y}^*$ is the long-run average of Y_t/X_{t-1}, and g^* is the long-run average of the gross growth rate of the stochastic trend, $g_t := X_t/X_{t-1}$. μ_t is an aggregate shock to interest rates.

A reduced-form specification of the interest rates in the international financial market, as in equation (3.11), is widely used in small open economy models for business cycle studies, particularly when the models are intended to be first-order approximated with respect to aggregate shocks. (See Neumeyer and Perri (2005), Garcia-Cicco et al. (2010), and Chang and Fernández (2013), for example.) In equation (3.11), interest rates are determined to be higher when the economy's international debt is larger and the productivities of the economy are lower. In this respect, equation (3.11) reflects the theoretical implication of sovereign default models such as Arellano (2008) and Mendoza and Yue (2012) in a reduced-form manner.

3.3.7 Aggregate Shock Processes

The model economy is hit by five aggregate shocks: a stationary productivity shock z_t, a trend shock g_t, an interest rate shock μ_t, an illiquidity shock η_t, and an investment shock ν_t. I assume that each aggregate shock follows an AR(1) process as follows.

$$\begin{aligned}
\log z_t &= \rho_z \log z_{t-1} + \epsilon_t^z, \quad \epsilon_t^z \sim N(0, \sigma_z^2),\\
\log(g_t/g^*) &= \rho_g \log(g_{t-1}/g^*) + \epsilon_t^g, \quad \epsilon_t^g \sim N(0, \sigma_g^2),\\
\log \mu_t &= \rho_\mu \log \mu_{t-1} + \epsilon_t^\mu, \quad \epsilon_t^\mu \sim N(0, \sigma_\mu^2),\\
\log \eta_t &= \rho_\eta \log \eta_{t-1} + \epsilon_t^\eta, \quad \epsilon_t^\eta \sim N(0, \sigma_\eta^2), \quad \text{and}\\
\log \nu_t &= \rho_\nu \log \nu_{t-1} + \epsilon_t^\nu, \quad \epsilon_t^\nu \sim N(0, \sigma_\nu^2).
\end{aligned} \tag{3.13}$$

3.3.8 Market Clearing and Trade Balance

The market clearing conditions are specified as follows.

$$L_t = \bar{e}\bar{l}_t \quad \text{(labor market)}, \tag{3.14}$$

$$F_t - D_t = B_t \quad \text{(liquid asset market), and} \tag{3.15}$$

$$q_t = A_t \quad \text{(illiquid asset market)}. \tag{3.16}$$

By Walras' law, we can derive the following resource constraint (or, equivalently, the goods market clearing condition in the open economy) using equations (3.5), (3.7), (3.9), (3.14), (3.15), and (3.16).

$$C_t + I_t + \Phi(K_t, K_{t-1}) + \xi(1 + r_{t-1})B_{t-1} = Y_t + D_t - (1 + r_{t-1})D_{t-1}. \tag{3.17}$$

The trade balance of the economy TB_t is determined as follows.

$$\begin{aligned} TB_t &= Y_t - C_t - I_t - \Phi(K_t, K_{t-1}) - \xi(1 + r_{t-1})B_{t-1} \\ &= -D_t + (1 + r_{t-1})D_{t-1}. \end{aligned} \tag{3.18}$$

3.3.9 Equilibrium

Given the initial conditions on $\Psi_0(e_1, e_2, b_-, a_-)$, X_{-1}, A_{-1}, K_{-1}, D_{-1}, B_{-1}, F_{-1}, and r_{-1},[18]

i) individual households' policy functions $\{c_t(e_1, e_2, b_-, a_-), b_t(e_1, e_2, b_-, a_-), a_t(e_1, e_2, b_-, a_-)\}_{t=0}^{\infty}$ that solve the households' optimization problem (3.2),

ii) cross-sectional cumulative distributions $\{\Psi_t(e_1, e_2, b_-, a_-)\}_{t=1}^{\infty}$ that evolve over time according to equation (3.3),

[18] Referring back to footnote 15, state vector $\mathcal{S}_t$ is composed of predetermined objects $\Psi_t(e_1, e_2, b_-, a_-)$, X_{t-1}, A_{t-1}, K_{t-1}, D_{t-1}, B_{t-1}, F_{t-1}, and r_{t-1} and aggregate exogenous variables z_t, g_t, μ_t, η_t, and ν_t. The initial conditions in this subsection specify the predetermined objects of $\mathcal{S}_0$.

iii) aggregate variables $\{C_t, B_t, A_t, \chi_t^{agg}\}_{t=0}^{\infty}$ constructed by aggregating corresponding individual variables according to equation (3.4),

iv) prices and aggregate variables $\{r_t^b, r_t^a, r_t, w_t, q_t, \bar{l}_t, L_t, \Pi_t, Y_t, I_t, K_t, F_t, D_t, \hat{D}_t, TB_t\}_{t=0}^{\infty}$ satisfying firms' optimality conditions (including constraints) for their optimization problem (3.8) and other equilibrium conditions (3.6), (3.7), (3.9), (3.11), (3.12), (3.14), (3.15), (3.16), and (3.18), and

v) aggregate shocks $\{z_t, g_t, \mu_t, \eta_t, \nu_t\}_{t=0}^{\infty}$, which follow the processes specified in (3.13)

constitute the equilibrium of the economy.

3.3.10 Solving the Model

To study business cycles through Bayesian estimation, we need to solve a model a large number of times. To this end, a model needs to be solved quickly (at least within a second). My model is a heterogeneous-agent model with aggregate uncertainty, and it only recently became possible to solve this class of models within a second thanks to the development of new computational methods.[19]

Among the new computational methods developed, I adopt Auclert et al. (2019)'s method, which computes the linearized dynamics of the macroeconomic variables (including aggregate quantities and prices) based on Boppart et al. (2018)'s finding that the impulse responses after an MIT shock are equivalent to the MA(∞) representation of the first-order-approximated model with aggregate uncertainty. Under this method, deviations of the macroeconomic variables from the balanced growth path caused by aggregate uncertainty are linearized, while the nonlinearity of individual households' decisions with respect to idiosyncratic uncertainty on the balanced growth path is still preserved. Since this method uses the impulse responses after an MIT shock (*i.e.*, no aggregate uncertainty after a one-time shock) to recover the linearized dynamics of the original economy with aggregate uncertainty, in Appendix C.2.1, I recharacterize the equilibrium under

[19] The main contributors to the recent development include Auclert et al. (2019), Boppart et al. (2018), Ahn et al. (2018), Bayer and Luetticke (2020), Winberry (2018), and Reiter (2009).

the circumstance in which the economy is subject to deterministic paths of aggregate exogenous variables $\{z_t, g_t, \mu_t, \eta_t, \nu_t\}_{t=0}^{\infty}$.

Another important aspect in solving the model is that the quantity variables in the economy inherit the stochastic trend, and thus, we need to detrend the equilibrium to make it stationary. In Appendix C.2.2, I detrend the quantity variables and define a stationary detrended equilibrium under deterministic paths of $\{z_t, g_t, \mu_t, \eta_t, \nu_t\}_{t=0}^{\infty}$. I then solve the detrended equilibrium using Auclert et al. (2019)'s method. Appendix C.2.3 briefly describes how the method works to solve the equilibrium. Once the detrended equilibrium is solved, we can recover the original equilibrium. Appendix C.2.4 discusses how to recover the statistics of the original equilibrium from the detrended equilibrium.

3.4 Taking the Model to the Data

The goal of this chapter is to study the stylized patterns of emerging market business cycles appearing in macro data through the lens of a model that incorporates the degree of household heterogeneity and consumption responses appearing in micro data. To achieve this goal, I employ both calibration and Bayesian estimation. First, I calibrate a subset of parameters to match the key empirical moments from the micro data. These micro moments include i) the estimates of the labor income process, which is the ultimate source of household heterogeneity in the model, and ii) the MPC estimates over the labor income deciles, which capture the degree of households' consumption responses.[20] Then, I estimate the rest of the parameters using Bayesian methods and macro data. The parameters governing the exogenous shock processes are estimated in this step. Through this Bayesian estimation, I run a horse race among different aggregate shocks to identify the main drivers of emerging market business cycles. Conventional candidates in the literature, including trend shocks and interest rate shocks, are included in the race. Note that this two-step estimation procedure (calibration in the first step, Bayesian estimation in the second

[20]There are also parameters that I calibrate either by matching the long-run average statistics from the macro data or by adopting commonly used values in the literature on emerging market business cycles, as we shall see in the following subsection.

step) is possible because the calibration in the first step is conducted by targeting moments on the balanced growth path, and the Bayesian-estimated parameters in the second step do not affect the balanced growth path of the economy.

3.4.1 Calibration

The time unit in the model is meant to be one quarter. Table 3.1 reports the calibrated parameters, calibrated values, and a brief description of the target moments or sources of information used for the calibration. The parameters governing the labor income process are ρ_{e_1}, σ_{e_1}, and σ_{e_2}. These parameters are calibrated by applying Floden and Lindé (2001)'s method to the labor income data from ENAHO, as discussed in Appendix C.1.1 .

On the balanced growth path, r_t^a, r_t^b, and r_t are all equal to r^*. (See Appendix C.2.2.3 for details.) I calibrate r^* by matching the long-run average of the real lending rates in the data, 0.022. The real lending rate series are constructed by deflating the data series on quarterly nominal lending rates for foreign-currency-denominated assets in 1992Q1-2017Q1 from International Financial Statistics (IFS, hereafter) with the expected inflation on U.S. CPIs.[21] [22]

Parameter ξ is calibrated such that the liquid asset return $(1-\xi)(1+r^*)$ is matched with the long-run average value of the real deposit rates in the data, 0.001. The real deposit rate series are constructed by deflating the data series on the quarterly nominal deposit rates for foreign-currency-

[21]The expected inflation is constructed by taking the average of inflation rates in the current and past three quarters, following Neumeyer and Perri (2005) and Uribe and Yue (2006). Atkeson and Ohanian (2001) provide empirical evidence supporting this practice.

[22]In the literature on emerging market business cycles, interest rate series are often constructed by adding J.P. Morgan's EMBIG spreads of sovereign bonds with real interest rates of U.S. 3-month Treasury Bills. ('EMBIG interest rates' in this footnote). Instead, I construct real interest rates based on IFS data series ('IFS interest rates' in this footnote). I find that the EMBIG interest rates and the IFS interest rates are highly correlated (correlation 0.843), but their means are substantially different. In terms of the (nonannualized) quarterly rate, the mean of the EMBIG interest rates is 0.007, while the mean of the IFS interest rates is 0.022. Given that the long-run average trade-balance-to-output ratio in the model is targeted to its data counterpart, there is a one-to-one relationship between r^* and the ratio of net foreign asset position (NFA, hereafter) to output, $-D_t/Y_t$ on the balanced growth path through the following equation: $r^* = \frac{TB_t/Y_t}{D_t/Y_t} g^* + (g^*-1)$. (This equation comes from equation (C.66) in Appendix C.2.2.3.) Using this equation, I recover the value of r^* that gives the exact long-run average value of the Peruvian NFA-to-output-ratio in Milesi-Ferretti and Lane (2017)'s dataset. The value of this r^* is 0.025, which is much closer to the mean of the IFS rates than to the mean of the EMBIG rates. Based on this observation, I use IFS interest rates instead of EMBIG interest rates so that the model generates (D_t/Y_t) close to Milesi-Ferretti and Lane (2017)'s debt data on the balanced growth path.

Table 3.1: Calibrated Parameters for the Peruvian Economy

	Description	Value	Target / source
labor income process			
ρ_{e_1}	persistence of the AR(1) component	0.968	ENAHO
σ_{e_1}	S.D. of shocks to the AR(1) component	0.128	ENAHO
σ_{e_2}	S.D. of shocks to the $i.i.d.$ component	0.470	ENAHO
long-run averages			
g^*	long-run average gross growth rate	1.004	$E[Y_t/Y_{t-1}]$
r^*	long-run average lending rate	0.022	IFS, U.S. CPI
ξ	long-run average spread	0.020	IFS, U.S. CPI
α	capital income share	0.385	$(K/Y)(r^* + \delta)/g^*$
δ	depreciation rate	0.014	$g^*(I/Y)/(K/Y) - (g^* - 1)$
parameters from the literature			
γ	inverse of IES	2.000	Garcia-Cicco et al. (2010)
ω	inverse of labor supply elasticity	0.600	Garcia-Cicco et al. (2010)
κ	scale parameter of labor disutility	4.038	$L = 1$ on the b.g.p
targeting MPCs over the labor income deciles & Aggregate Wealth			
β	discount factor	0.948	MPC estimates (from ENAHO) and TB/Y
χ_1	scale parameter of illiquid adj. cost	1.347	MPC estimates (from ENAHO) and TB/Y
χ_2	convexity parameter of illiquid adj. cost	1.496	MPC estimates (from ENAHO) and TB/Y
χ_0	non-zero denom. in illiquid adj. cost	0.010	

Notes: The time unit is one quarter. The abbreviation 'b.g.p' in the 'Target/source' column of parameter κ represents the balanced growth path of the equilibrium.

denominated assets in 1992Q1-2017Q1 from IFS with the expected inflation on U.S. CPIs.

There are other parameters that I calibrate by matching the long-run average statistics from macro data. Parameter g^* is calibrated by matching the long-run average value of (Y_t/Y_{t-1}) in the quarterly national accounts in 1980-2018 from Banco Central de Reserva del Perú (BCRP, hereafter). Parameter α is calibrated by using the following equation on the balanced growth path: $r^* + \delta = \alpha g^*(Y_t/K_t)$.[23] Specifically, I compute the long-run average value of the capital-to-output ratio using the annual capital stock and output series in 1980-2017 from Feenstra, Inklaar, and Timmer (2015)'s Penn World Table (version 9.1). I transform the average annual capital-to-output ratio to a quarterly ratio by multiplying by four and obtain a value of 10.906. Parameter

[23]This equation comes from (C.54) in Appendix C.2.2.3.

δ is calibrated using another equation on the balanced growth path: $\delta + g^* - 1 = g^* \frac{I_t/Y_t}{K_t/Y_t}$.[24] The long-run average investment-to-output ratio is computed using the quarterly national accounts in 1980-2018 from BCRP, and I obtain a value of 0.191.

Parameters γ and ω are assigned the values used in Garcia-Cicco et al. (2010), which are common in related business cycle studies. Parameter κ is calibrated such that aggregate labor supply is normalized to be one on the balanced growth path.

Given the parameter values assigned above, parameters β, χ_1, and χ_2 are calibrated by targeting the ten MPC estimates over the labor income deciles and the aggregate wealth of the economy (or, equivalently, the aggregate amount of households' asset holdings $A_t + B_t$) on the balanced growth path.[25] [26] Specifically, I implement this calibration by minimizing the following objective function J:

$$\begin{aligned} J =& w_{TB/Y}\left\{(TB/Y)_{model} - (TB/Y)_{data}\right\}^2 \\ &+ (1 - w_{TB/Y})\left\{\sum_{j=1}^{10} w_{d_j}^{LY}(MPC_{d_j,model} - MPC_{d_j,data})^2\right\} \end{aligned}$$

in which $w_{TB/Y}$ denotes the weight on the first target (TB/Y), $(TB/Y)_{model}$ and $(TB/Y)_{data}$ denote the trade-balance-to-output ratio on the balanced growth path of the model and its long-run average value in the data, respectively, $w_{d_j}^{LY}$ denotes the share of labor income in the j-th labor income decile d_j in the model, $MPC_{d_j,model}$ is the model-generated MPC in decile d_j, and $MPC_{d_j,data}$ is the MPC estimate of decile d_j in the data.

In constructing the objective function J, I target the trade-balance-to-output ratio instead of the wealth-to-output ratio $(A_t + B_t)/Y_t$. I do so because there are no direct data on aggregate wealth, $A_t + B_t$. Given that there exist data on the capital-to-output ratio K_t/Y_t and trade-balance-to-output ratio TB_t/Y_t, however, the following long-run relationship among stock variables of the model

[24] This equation comes from (C.53) in Appendix C.2.2.3.

[25] As discussed in subsection 3.3.1, χ_1 and χ_2 affect both MPCs and aggregate wealth.

[26] For χ_0, I assign an arbitrary small number, 0.01, as the sole purpose of including the term $\chi_0 X_{t-1}$ in the functional form of $\chi_t(v_{i,t}, a_{i,t-1})$ is to ensure that the denominator of $\left(\frac{v_{i,t}}{(1+r_t^a)a_{i,t-1}+\chi_0 X_{t-1}}\right)$ is nonzero.

disciplines what the correct amount of aggregate wealth is.

$$(K_t/X_t) + \left(\frac{\chi_t^{agg}}{1 + r_{ss} - g_{ss}} \frac{1}{X_t}\right) = (A_t/X_t) + (B_t/X_t) + (D_t/X_t) \quad \text{on the b.g.p}$$

$$\Leftrightarrow (K_t/Y_t) + \left(\frac{\chi_t^{agg}}{1 + r^* - g^*} \frac{1}{Y_t}\right) = (A_t/Y_t) + (B_t/Y_t) + (D_t/Y_t) \quad \text{on the b.g.p}$$

$$\Rightarrow (K_t/Y_t) - \frac{g^*}{1 + r^* - g^*}(TB_t/Y_t) = (A_t/Y_t) + (B_t/Y_t) - \left(\frac{\chi_t^{agg}}{1 + r^* - g^*} \frac{1}{Y_t}\right) \quad \text{on the b.g.p}$$

in which b.g.p denotes the balanced growth path.[27] In the last equation, I target the model-generated value of the right-hand-side toward the data counterpart on the left-hand-side. Such calibration can be achieved by targeting TB_t/Y_t only because in the step of calibrating α, the model's long-run average value of K_t/Y_t is already matched with the data. I compute the long-run average value of TB_t/Y_t using the quarterly national accounts in 1980-2018 from BCRP and obtain a value of 0.043.

After the calibration of β, χ_1, and χ_2, the model generates both a trade-balance-to-output ratio and an MPC graph over the labor income deciles that are quite similar to their data counterparts, despite the fact that I only use three parameters to target eleven moments. First, the model-generated trade-balance-to-output ratio on the balanced growth path is 0.042, and its data counterpart is 0.043. Second, the model-generated MPCs over the labor income deciles are plotted as a thick black solid line in Figure 3.2.[28] In this figure, the blue solid line with circle markers and the shaded area around the line represent the quarterly MPC estimates from ENAHO and their 95% confidence intervals, respectively.[29] As this figure shows, the MPC graph generated from the model closely tracks the MPC estimates from the data.

There is one additional noteworthy observation here. After the calibration, the aggregate wealth

[27]The first line comes from equation (C.69), and the derivation of the third line from the second line comes from equation (C.66) in Appendix C.2.2.3.

[28]The model-generated MPCs of the labor income deciles are computed by simulating the consumption and income of 1,000,000 households over nine quarters, constructing year-over-year growth of consumption and income over two consecutive years, and applying to the simulated data the exactly same MPC estimation procedure applied to the actual data (ENAHO).

[29]The blue solid line with circle markers and the shaded area around the line in Figure 3.2 are identical to those in Figure 3.1.

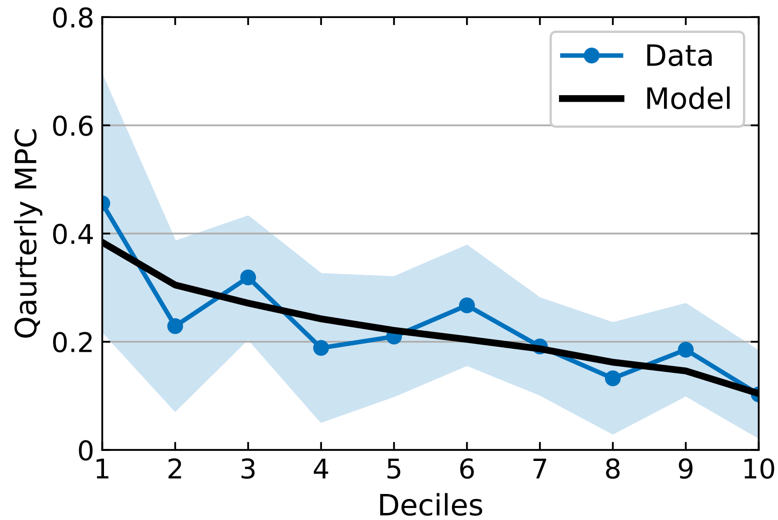


Figure 3.2: Quarterly MPCs in Peru: Data vs Model

Notes: Figure 3.2 plots the quarterly MPC estimates from ENAHO and their model counterparts under the calibration targeting the estimated Peruvian MPC graph.

is saved almost entirely in the form of illiquid assets. On the balanced growth path, the aggregate amount of illiquid assets is 51 times greater than that of liquid assets. This outcome reflects how households optimize when they face a large spread between liquid asset and illiquid asset return rates: the latter (0.022) is approximately 22 times greater than the former (0.001) on the balanced growth path.

3.4.2 Bayesian Estimation

I estimate model parameters ψ (the debt elasticity of interest rates in the international financial market), ϕ (the parameter governing the capital adjustment cost), θ_z and θ_g (the sensitivities of interest rates in the international financial market to stationary and nonstationary productivity shocks) as well as parameters governing aggregate shock processes ρ_z, σ_z, ρ_g, σ_g, ρ_μ, σ_μ, ρ_η, σ_η, ρ_ν, and σ_ν using Bayesian methods. Following previous studies that apply Bayesian methods to estimate representative-agent small open economy models using emerging market macro data, such as Garcia-Cicco et al. (2010) and Chang and Fernández (2013), I employ aggregate output, consumption, investment, and trade-balance-to-output ratio series for the Bayesian estimation. These macro data series are from the quarterly national accounts of BCRP in the period 1980-2018.

Two specific details are worth noting in determining the counterparts between the model and the data for the estimation. First, financial intermediation services $\zeta(1+r_{t-1})B_{t-1}$ in the model must be designated either as final consumption or as intermediate consumption in national accounting. I assume that they are designated as final consumption. Under this assumption, the model counterpart of the final consumption in the national accounts, which I denote by C_t^{msd}, is determined as follows. [30]

$$C_t^{msd} := C_t + \xi(1 + r_{t-1})B_{t-1}.$$

If the financial intermediation services are instead designated as intermediate consumption, the model counterpart of output in the national accounts becomes $Y_t - \zeta(1 + r_{t-1})B_{t-1}$ (in which Y_t is gross value-added and $\zeta(1 + r_{t-1})B_{t-1}$ is intermediate consumption). However, because $\zeta(1 + r_{t-1})B_{t-1}$ is very small relative to C_t and Y_t in the model and does not fluctuate substantially in equilibrium, whether $\zeta(1 + r_{t-1})B_{t-1}$ is designated as final consumption or intermediate consumption has no meaningful effect on the results.[31]

Second, I use log output growth ($\Delta \log Y_t$), log consumption growth ($\Delta \log C_t^{msd}$), log investment growth ($\Delta \log I_t$), and the first difference of the trade-balance-to-output ratio ($\Delta TB_t/Y_t$) in taking the model to the data, as in Chang and Fernández (2013). Garcia-Cicco et al. (2010) use the same set of statistics except for using TB_t/Y_t instead of $\Delta TB_t/Y_t$. Both choices are acceptable from a statistical perspective, as neither of them inherits a trend in the data and the model. I choose $\Delta TB_t/Y_t$ over TB_t/Y_t because the countercyclicality of the trade balance, which is a common pattern for both emerging and developed economies, is better reflected in the estimation when $\Delta \log Y_t$ is correlated with $\Delta TB_t/Y_t$ rather than with TB_t/Y_t.

[30] Superscript *msd* abbreviates 'measured'.

[31] In real-world national accounting, financial intermediation services are labeled Financial Intermediation Services Indirectly Measured (FISIM) and measured as follows. First, 'reference rates' are determined according to specific rules such that they are located between lending rates and deposit rates. Second, FISIM is defined as the sum of the following two components: the amount of deposits multiplied by the spread between reference rates and deposit rates and the amount of loans multiplied by the spread between reference rates and lending rates. Third, the former component is designated as the final consumption of depositors, while the latter component is designated as the intermediate consumption of borrowers. Therefore, my assumption of assigning $\zeta(1 + r_{t-1})B_{t-1}$ to final consumption is equivalent to assuming that the statistical agency determines the reference rates as r_t.

For the Bayesian estimation, I implement the Random Walk Metropolis-Hastings (RWMH) algorithm described in Herbst and Schorfheide (2015). Specifically, I construct the posterior distribution by sampling 500,000 draws through the RWMH algorithm and burning the initial 100,000 draws. A successful implementation of the algorithm requires i) a good variance-covariance matrix of the proposal distribution, which should be close to the variance-covariance matrix of the posterior distribution itself after scaling, and ii) the correct scaling factor for the matrix, which achieves an acceptance rate in the range 0.2-0.4. To this end, I run multiple preliminary stages of the RWMH algorithm and its variant before the main RWMH algorithm through which i) the draws of the chain move closer to the posterior mode, ii) the variance-covariance matrix of the proposal distribution is updated to become closer to the variance-covariance matrix of the posterior distribution after scaling, and iii) the scaling factor is updated to achieve the target acceptance rate of 0.27.[32]

I impose a fairly flat prior distribution, as reported in the left vertical panel of Table 3.2. Regarding the autocorrelation coefficients of the exogenous shock processes ρ_z, ρ_g, ρ_μ, ρ_η, and ρ_ν, I assume that they follow a beta distribution after being scaled by (1/0.99) in the prior. The scaling is to ensure that the autocorrelation coefficients do not exceed 0.99 under any posterior draw, as the precision of Auclert et al. (2019)'s computation method becomes compromised when the economy becomes too persistent.[33] I set the mean and standard deviation of the beta distribution as 0.5 and 0.2, respectively, for all the autocorrelation coefficients except ρ_g. For ρ_g, I use 0.3 as the mean of the beta distribution, reflecting the conventional view that trend shocks are transitory.[34]

The standard deviations of the exogenous shock processes, σ_z, σ_g, σ_μ, σ_η, and σ_ν, follow an inverse gamma distribution with a mean of 0.01 and a standard deviation of 0.02 in the prior distribution. For the parameter governing the capital adjustment cost, ϕ, I impose a gamma distribution

[32]The acceptance rate of the main RWMH algorithm is 0.271, which is close to the target.

[33]An acceptable degree of persistence depends on the length of the sequence used in Auclert et al. (2019)'s sequence-space approach. I set the sequence length as $T = 300$. (See Appendix C.2.3 for a brief description of how their sequence space approach works.) Auclert et al. (2019) report that their two-asset HANK model, which has an almost identical household block to my model, can be solved within an acceptable range of precision under an autocorrelation coeffieicnt of 0.99 for the stationary productivity shock.

[34]See Aguiar and Gopinath (2007) and Garcia-Cicco et al. (2010), for example.

Table 3.2: Prior and Posterior Distributions of the Bayesian Estimation

	Prior Distribution		Posterior Distribution		
	density	[meta1, meta2]	mean	S.D.	[0.05, 0.95]
ψ	Uniform	[0.000,2.000]	1.623	0.294	[1.051,1.975]
ϕ	Gamma	[15.000,15.000]	11.863	2.365	[8.073,15.854]
θ_z	Uniform	[0.000,2.000]	0.374	0.181	[0.091,0.692]
θ_g	Uniform	[0.000,2.000]	0.622	0.504	[0.035,1.651]
ρ_z	0.99·Beta	[0.500,0.200]	0.849	0.034	[0.794,0.905]
σ_z	Invgamma	[0.010,0.020]	0.017	0.001	[0.015,0.019]
ρ_g	0.99·Beta	[0.300,0.200]	0.880	0.105	[0.725,0.960]
σ_g	Invgamma	[0.010,0.020]	0.003	0.001	[0.002,0.004]
ρ_μ	0.99·Beta	[0.500,0.200]	0.484	0.198	[0.160,0.809]
σ_μ	Invgamma	[0.010,0.020]	0.005	0.002	[0.002,0.009]
ρ_η	0.99·Beta	[0.500,0.200]	0.835	0.147	[0.527,0.960]
σ_η	Invgamma	[0.010,0.020]	0.329	0.053	[0.243,0.418]
ρ_ν	0.99·Beta	[0.500,0.200]	0.451	0.129	[0.237,0.663]
σ_ν	Invgamma	[0.010,0.020]	0.036	0.008	[0.025,0.050]
σ_y^{me}	Uniform	[0.000,0.007]	0.006	0.000	[0.006,0.007]
σ_c^{me}	Uniform	[0.000,0.009]	0.009	0.000	[0.008,0.009]
σ_i^{me}	Uniform	[0.000,0.045]	0.044	0.001	[0.043,0.045]
σ_{tby}^{me}	Uniform	[0.000,0.004]	0.004	0.000	[0.004,0.004]

Notes: Estimation is based on the quarterly national accounts of Peru in the period 1980-2018. In the prior density column, '0.99 · Beta' means that the corresponding parameter multiplied by (1/0.99) follows a beta distribution. The column labeled '[meta1,meta2]' reports the meta parameters of the prior distributions. For a uniform distribution, [meta1,meta2] is [lower bound, upper bound]. For inverse gamma distribution and gamma distribution, [meta1,meta2] is [mean, standard deviation]. For '0.99 · Beta', [meta1,meta2] is [mean, standard deviation] of the beta distribution part. Posterior statistics are based on 500,000 posterior draws from the RWMH algorithm, of which the initial 100,000 draws are burned.

with a mean of 15.0 and a standard deviation of 15.0 in the prior distribution. For the rest of the parameters, I impose uniform distributions.

The parameters in the last four rows of Table 3.2, σ_y^{me}, σ_c^{me}, σ_i^{me}, and σ_{tby}^{me} represent the standard deviations of the measurement errors for $\Delta \log Y_t$, $\Delta \log C_t^{msd}$, ΔI_t, and $\Delta TB_t/Y_t$, respectively. I allow these measurement errors to explain up to 6.25% of the variances of the observed variables.

The right vertical panel of Table 3.2 reports key statistics of the posterior distribution, including the mean, standard deviation, 5th percentile, and 95th percentile of the marginal posterior distribution of each parameter. I highlight three notable features. First, the posterior means of σ_g and

σ_μ are very small, implying that trend shocks and interest rate shocks might not play an important role in explaining emerging market business cycles in my model. Second, θ_g is weakly identified, which is understandable given that I do not employ interest rate series for the estimation.[35] As we shall see in sections 3.5 and 3.6, however, the key model statistics of this chapter do not inherit the weak identification of θ_g because σ_g is very small. Third, the posterior mean of ρ_η is 0.835, which is as large as that of ρ_z. Moreover, the posterior mean of σ_η is 0.329, which is markedly large. The combination of the high degree of persistence and the large standard deviation suggests that illiquidity shocks (η_t) might play an important role in accounting for the business cycles. Of course, we cannot compare which shocks are more important by simply comparing the autocorrelation coefficients and standard deviations because they hit different objects of different sizes in the economy. The variance decomposition in subsection 3.6.1 provides a formal comparison of the relative importance of the shocks in explaining the business cycles.

3.4.3 Model Performance

Table 3.3 compares key business cycle moments between the model and the data after the Bayesian estimation. This table shows that i) the Peruvian macro data exhibit the stylized patterns of emerging market business cycles, and ii) the model simulates these patterns quite well.

First, the standard deviation of output growth is 0.027 in the Peruvian data. This number is far beyond the average standard deviation of output growth in rich countries, 0.008, reported in Table 1.6 of Uribe and Schmitt-Grohé (2017). In other words, the Peruvian data exhibit the stylized pattern of emerging economies whereby output volatility is substantially greater than that of developed economies. The model simulates this pattern well by generating an output growth volatility of 0.029, which is similar to the data counterpart.

Second, the Peruvian data exhibit the stylized pattern of emerging economies whereby consumption is more volatile than output (excess consumption volatility): the standard deviation of

[35] As in Aguiar and Gopinath (2007), Garcia-Cicco et al. (2010), and Chang and Fernández (2013), interest rate series are not used for the estimation because they are available only for substantially shorter time periods than other observable variables.

Table 3.3: Standard Deviations and Correlations: Model vs Data

		$\Delta \log Y_t$	$\Delta \log C_t^{msd}$	$\Delta \log I_t$	$\Delta(TB_t/Y_t)$
standard deviation					
	model	0.029	0.037	0.140	0.017
	data	0.027	0.036	0.179	0.017
contemporaneous correlation					
with $\Delta \log Y_t$	model		0.668	0.472	-0.229
	data		0.682	0.437	-0.346
with $\Delta(TB_t/Y_t)$	model		-0.325	-0.539	
	data		-0.318	-0.460	
with $\Delta \log C_t^{msd}$	model			-0.155	
	data			-0.158	
autocorrelation					
with lag 1	model	-0.035	-0.035	-0.153	0.010
	data	0.404	0.078	-0.304	0.023
with lag 2	model	-0.027	-0.052	-0.078	-0.090
	data	0.009	0.036	-0.094	-0.077
with lag 3	model	-0.020	-0.049	-0.046	-0.099
	data	-0.090	-0.112	0.026	-0.061

Notes: The model statistics are computed under each posterior draw, and the means over the posterior distribution are reported in this table.

consumption growth (0.036) is markedly greater than the standard deviation of output growth (0.027) in the Peruvian data. The model again simulates this stylized pattern well by generating a standard deviation of consumption growth (0.037) that is substantially greater than the standard deviation of output growth (0.029).

In addition to these well-known stylized patterns of emerging market business cycles, the model also closely matches other business cycle moments reported in Table 3.3, including the standard deviations of other variables, contemporaneous correlations, and autocorrelations.[36] In Appendix

[36]One exception is the autocorrelation of $\Delta \log Y_t$ with a one-quarter lag: the model yields -0.035, which is noticeably smaller than the data counterpart, 0.404. However, this discrepancy quickly dissipates from a two-quarter lag forward. Given that this discrepancy survives only one quarter and that output growth variations almost entirely come from stationary productivity shocks, as we shall see in subsection 3.6.1, it is likely that replacing the conventional AR(1) process of stationary productivity shocks with an ARMA(1,1) process can fix this discrepancy. I do not impose this unconventional assumption, however, because the model aims to minimize changes from the conventional representative-agent models other than the heterogeneous household block with high MPCs.

C.3, I further compare the cross-autocorrelograms between the model and the data and find that the model again closely mimics the data.

I highlight one more moment in Table 3.3 for later discussion, although it has received less attention in the literature to date. The correlation between consumption growth and investment growth is substantially lower than one in the Peruvian data.[37] Moreover, low correlation between consumption growth and investment growth is not an abnormal phenomenon of the Peruvian data: I find that the correlation of emerging countries is 0.189 on average and that of developed countries is 0.278 on average.[38] The model successfully simulates this pattern by generating a correlation (-0.158) that is substantially lower than one.

3.5 Counterfactual Experiment

To what extent do high-MPC households (or, more precisely, the environment that makes households exhibit high MPCs) contribute to the large consumption volatility of emerging economies? To answer this question, I conduct a counterfactual experiment in which I replace the Peruvian households with those exhibiting the U.S. MPCs. I then examine whether the phenomenon of excess consumption volatility survives.

To this end, I recalibrate the parameters that I use to target the Peruvian MPCs in the baseline calibration, including the parameters governing the adjustment cost for illiquid assets (χ_1 and χ_2) and the time discount factor (β). These parameters are recalibrated by targeting the ten MPC estimates of the U.S. labor income deciles from the PSID and the Peruvian trade-balance-to-output ratio.[39] As discussed in subsection 3.4.1, targeting the trade-balance-to-output ratio disciplines

[37]It is indeed negative in the Peruvian data, but as we shall see in the later discussion, what matters in this chapter is not its being negative but being substantially less than one.

[38] In computing the average correlation for emerging countries and developed countries, I use the quarterly macro data series and country categorization used for the business cycle statistics in the first chapter of Uribe and Schmitt-Grohé (2017). From the data set, sample countries are selected if all five data series of output, investment, exports, imports, and consumption are available for at least twenty years. After the sample selection, 16 emerging countries and 17 rich countries remain in the sample. In averaging the correlation over multiple countries, I use population weights.

[39]Although χ_1, χ_2, and β are important determinants of the MPCs in the model, there are other parameters that also affect MPCs. Such parameters include the difference in return rates between liquid and illiquid assets ξ and the parameters governing the labor productivity process ρ_{e_1}, σ_{e_1}, and σ_{e_2}. In Appendix C.4, I run an alternative

Table 3.4: Recalibrated Parameters for the Counterfactual Economy

	Description	Value	Target / source
targeting MPCs over the labor income deciles & Aggregate Wealth			
β	discount factor	0.968	MPC estimates (from PSID) and Peruvian TB/Y
χ_1	scale parameter of illiquid adj. cost	0.246	
χ_2	convexity parameter of illiquid adj. cost	1.366	

the model to have the correct amount of aggregate wealth on the balanced growth path. I target the Peruvian (not U.S.) trade-balance-to-output ratio because the recalibration aims to minimize changes in the economy other than households' MPCs. In targeting the U.S. MPC estimates from the PSID, I face a frequency mismatch problem between the model and the data: the PSID provides annual income and consumption, while one period is set equal to one quarter in the model. This frequency mismatch problem is addressed as follows: I simulate annual consumption and income series by aggregating model-generated quarterly consumption and income series over every four quarters and then apply to the simulated annual data the same MPC estimation procedure applied to the PSID data.[40] By doing so, I directly target the annual MPC estimates from the PSID rather than targeting the quarterized estimates according to Auclert (2019)'s model-free frequency conversion formula presented in section 3.2.

Table 3.4 reports the values of the recalibrated parameters. The value of χ_1 (0.246) under the recalibration is markedly lower than the value (1.347) under the baseline calibration in Table 3.1. This is because the U.S. MPC estimates discipline the model to exhibit lower MPCs than the Peruvian MPC estimates do. As discussed in subsection 3.3.1, a lower value of χ_1 weakens financial frictions and thus decreases the MPCs of households. On the other hand, the value of β (0.968) under the recalibration is noticeably greater than the value (0.948) under the baseline

counterfactual experiment in which these parameters are also recalibrated. Specifically, I recalibrate ξ, ρ_{e_1}, σ_{e_1}, and σ_{e_2} using relevant U.S. data first and then recalibrate χ_1, χ_2, and β by targeting the U.S. MPC estimates and the Peruvian trade-balance-to-output ratio. I find that the results do not change in any meaningful way.

[40] Specifically, the PSID provides two-year-over-two-year growth of annual income and consumption because the survey is conducted biannually, and each wave provides only one annual consumption and income. To create the same data structure, I simulate the consumption and income of 1,000,000 households over twenty quarters, convert the twenty-quarter quarterly series into five-year annual series by aggregating them over every four quarters, and construct two consecutive two-year-over-two-year growth rates of annual income and consumption. I then apply the same estimation procedure used in the PSID to the simulated data.

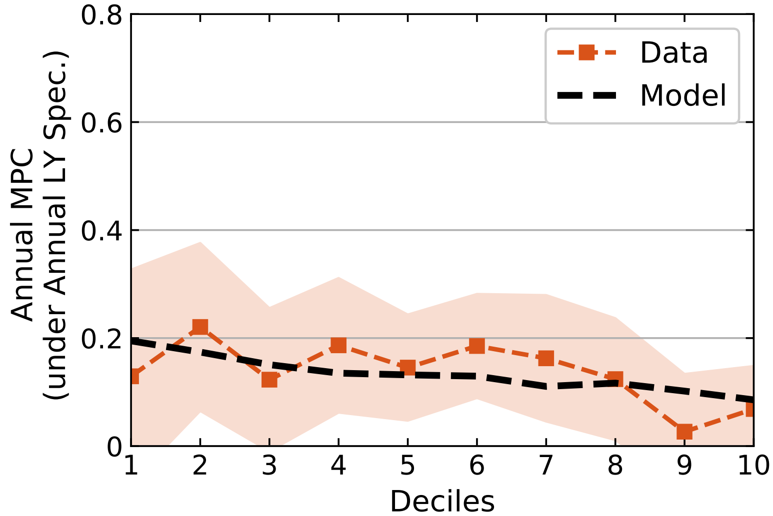


Figure 3.3: Annual MPCs in U.S.: Data vs Model

Notes: Figure 3.3 plots the annual MPC estimates from the PSID and their model counterparts under the calibration targeting the estimated U.S. MPC graph. In computing the model counterparts of the estimates, I simulate annual consumption and income series by aggregating model-generated quarterly consumption and income series over every four quarters and then apply to the simulated annual data the same MPC estimation procedure applied to the PSID data.

calibration. This is because households save less under the lower value of χ_1 as discussed in subsection 3.3.1, and this weaker saving due to the lower value of χ_1 needs to be compensated by a higher value of β to match the correct amount of aggregate wealth in the counterfactual economy.

After the recalibration, both the model-generated trade-balance-to-output ratio and the MPC graph over the labor income deciles closely match their data counterparts in the counterfactual economy. The model-generated trade-balance-to-output ratio on the balanced growth path is 0.041, and its data counterpart is 0.043. The model counterparts of the U.S. MPC estimates are plotted as a thick black dashed line in Figure 3.3. In this figure, the red dashed line with square markers and the shaded area around the line represent the the annual MPC estimates from the PSID and their 95% confidence intervals, respectively.[41] As this figure shows, the model-generated MPC graph closely tracks the estimates from the PSID.

Referring back to the problem of time-frame inconsistency under the model-free frequency

[41] The red dashed line with square markers and the shaded area around the line in Figure 3.3 are different from those in Figure 3.1 because the latter is the quarterized version of the former according to equation (3.1).

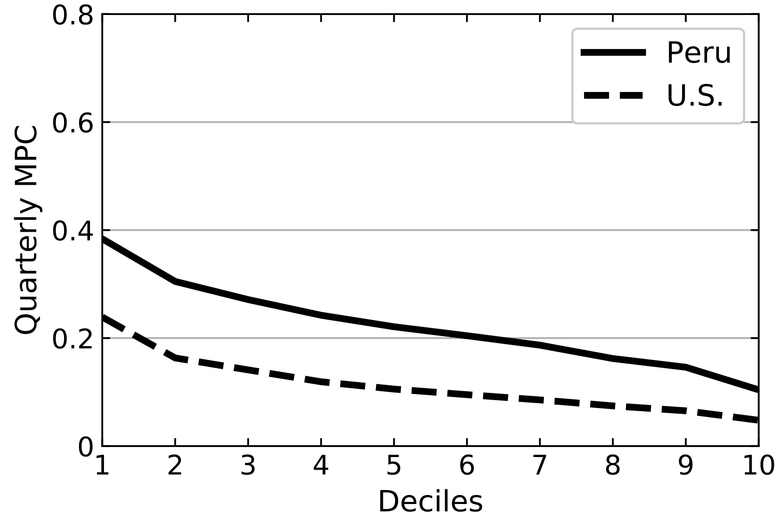


Figure 3.4: Model-Predicted Quarterly MPCs: Peru and U.S.

Notes: Figure 3.4 compares the model-predicted quarterly MPCs between the baseline economy, which is calibrated by targeting the quarterly Peruvian MPC estimates, and the counterfactual economy, which is calibrated by targeting the annual U.S. MPC estimates.

conversion (3.1) in section 3.2, we can now compare Peruvian and U.S. MPCs without this problem by using the model. Figure 3.4 compares the model-predicted quarterly MPCs between the baseline economy, which is calibrated by targeting the quarterly Peruvian MPC estimates, and the counterfactual economy, which is calibrated by targeting the annual U.S. MPC estimates. Two important observations are made from the comparison between Figure 3.4 and Figure 3.1. First, the MPC gap between Peru and the U.S. predicted by the model in Figure 3.4 is narrower than that predicted by the model-free frequency conversion (3.1) in Figure 3.1. Second, despite this tendency, the model still predicts a substantial MPC gap between Peru and the U.S. In Figure 3.4, the population-weighted average of the Peruvian quarterly MPCs is 0.223, which is 2.0 times greater than that of the U.S. quarterly MPCs, 0.114. In terms of income-weighted averages, the average Peruvian quarterly MPC is 0.175, which is 2.1 times greater than the average U.S. MPC, 0.084.

Figure 3.4 suggests that the MPCs of Peruvian households are substantially higher than the MPCs of U.S. households when we interpret the MPC estimation results through the lens of the model. Now, we are ready to examine the business cycle implications of this MPC gap.

Table 3.5: The Absence of Excess Consumption Volatility in the Counterfactual Economy

	$\sigma(\Delta \log Y_t)$	$\sigma(\Delta \log C_t^{msd})$	$\frac{\sigma(\Delta \log C_t^{msd})}{\sigma(\Delta \log Y_t)}$
Baseline	0.029	0.037	1.283
	(0.002)	(0.002)	(0.075)
Counterfactual	0.028	0.027	0.963
	(0.002)	(0.002)	(0.069)

Notes: The statistics are computed under each posterior draw, and their means and standard deviations over the posterior distribution are reported in this table. The numbers in parentheses are the posterior standard deviations.

Table 3.5 compares the output growth volatility, consumption growth volatility, and the ratio of the two between the baseline economy and the counterfactual economy. As the first column shows, the output growth volatility of the counterfactual economy is similar to that of the baseline economy. In the model, output is solely determined by the firms' Cobb-Douglas production, $Y_t = z_t K_{t-1}^{\alpha}(X_t L_t)^{1-\alpha}$. Because K_{t-1} is a slow-moving variable and L_t is determined by z_t, X_t, and K_{t-1} (through the labor union's labor supply decision (3.6) and firms' hiring decision (C.15)), the processes of z_t and g_t almost entirely determine output volatility. Given this feature of the model, it is not surprising that output volatility is similar between the two economies.

Regarding consumption volatility, on the other hand, there is a substantial difference between the two economies. As reported in the second column of Table 3.5, the standard deviation of consumption growth is 0.027 in the counterfactual economy, which is 25.8% lower than that of the baseline economy, 0.037. As a consequence, the ratio between the consumption volatility and output volatility, $\frac{\sigma(\Delta \log C_t^{msd})}{\sigma(\Delta \log Y_t)}$, falls from 1.283 in the baseline economy to 0.963 in the counterfactual economy. In other words, the stylized pattern of emerging economies whereby consumption is more volatile than output, namely, excess consumption volatility, disappears once Peruvian households are counterfactually replaced with those with U.S. MPCs. This result strongly suggests that the high-MPC households in the Peruvian economy generate excess consumption volatility.

3.6 Driving Mechanisms

Through which mechanisms do the high-MPC households in emerging economies contribute to the large aggregate consumption volatility? To answer this question, this section conducts three decomposition exercises: variance decomposition, variance change decomposition, and consumption response decomposition.

3.6.1 Variance Decomposition

I begin by decomposing the variances of observable variables into the variances generated by each aggregate shock. Table 3.6 reports the result of this variance decomposition. To understand the variance decomposition result, in Figure 3.5, I plot the impulse responses of output (Y_t), consumption (C_t), investment (I_t), and the trade-balance-to-output ratio (TB_t/Y_t) in terms of their deviations from the balanced growth path after each one-standard-deviation aggregate shock.[42] [43]

Table 3.6 shows that output growth variations are almost entirely driven by stationary productivity shocks. To generate large variations in output growth (or equivalently, the first difference in log output), a shock should generate a large response on impact because an abrupt output change is needed. As the (1,3)-th, (1,4)-th, and (1,5)-th panels of Figure 3.5 suggest, interest rate shocks, illiquidity shocks, and investment shocks cannot generate any large output response on impact. Given this feature of the model, the actual candidates for output growth variations are stationary productivity shocks and trend shocks.

In the model of Aguiar and Gopinath (2007), representative households' strong consumption response to a trend shock on impact that is substantially stronger than the output response on impact is the key feature of the model that enables it to generate the stylized patterns of emerging market business cycles, including excess consumption volatility and a countercyclical trade bal-

[42] In the figures plotting the impulse responses of consumption, such as Figure 3.5, I plot the impulse responses of C, not C^{msd}. The differences between the impulse responses of C and those of C^{msd} are negligibly small.

[43] Appendix C.5 presents impulse responses for a more comprehensive set of model variables. In particular, Appendix C.5.1 presents the impulse responses in the baseline economy with 90-percent credible bands over the posterior distribution, and Appendix C.5.2 compares the impulse responses between the baseline economy and the counterfactual economy.

Table 3.6: Variance Decomposition

	$\Delta \log Y_t$	$\Delta \log C_t^{msd}$	$\Delta \log I_t$	$\Delta(TB_t/Y_t)$
stationary productivity shock (z_t)	0.961	0.423	0.228	0.075
	(0.019)	(0.051)	(0.048)	(0.040)
trend shock (g_t)	0.034	0.023	0.091	0.230
	(0.019)	(0.011)	(0.041)	(0.103)
interest rate shock (μ_t)	0.000	0.002	0.006	0.034
	(0.000)	(0.002)	(0.006)	(0.032)
illiquidity shock (η_t)	0.003	0.423	0.310	0.144
	(0.001)	(0.054)	(0.050)	(0.040)
investment shock (ν_t)	0.002	0.130	0.365	0.518
	(0.001)	(0.046)	(0.066)	(0.091)
total	1.000	1.000	1.000	1.000

Notes: The statistics of decomposed shares are computed under each posterior draw, and their means and standard deviations over the posterior distribution are reported in this table. The numbers in parentheses are the posterior standard deviations.

ance. Unlike this model, however, my model does not exhibit this feature. As seen from the (2,2)-th panel of Figure 3.5, the consumption response to a trend shock is not much greater than the output response on impact. Instead, the consumption response grows gradually in the subsequent periods as the output response does.[44] As a result, the ability of trend shocks to account for emerging market business cycles is significantly limited in my model, and the model assigns all the explanatory power for the output growth variations to stationary productivity shocks.

Regarding consumption growth variations, Table 3.6 shows that most of the variations are explained in equal parts by stationary productivity shocks and illiquidity shocks. To understand why illiquidity shocks are assigned a sizable explanatory power for consumption growth variations, we need to focus on the correlation between consumption growth and investment growth. As the (2,1)-th, (3,1)-th, (2,2)-th, (3,2)-th, (2,3)-th, and (3,3)-th panels of Figure 3.5 suggest, stationary productivity shocks, trend shocks, and interest rate shocks generate a strongly positive correlation between consumption growth and investment growth because the impact effects of these shocks on consumption and investment are in the same direction. However, as Table 3.3 shows, the correla-

[44] In the next section, I examine why trend shocks do not generate a strong consumption response in my model.

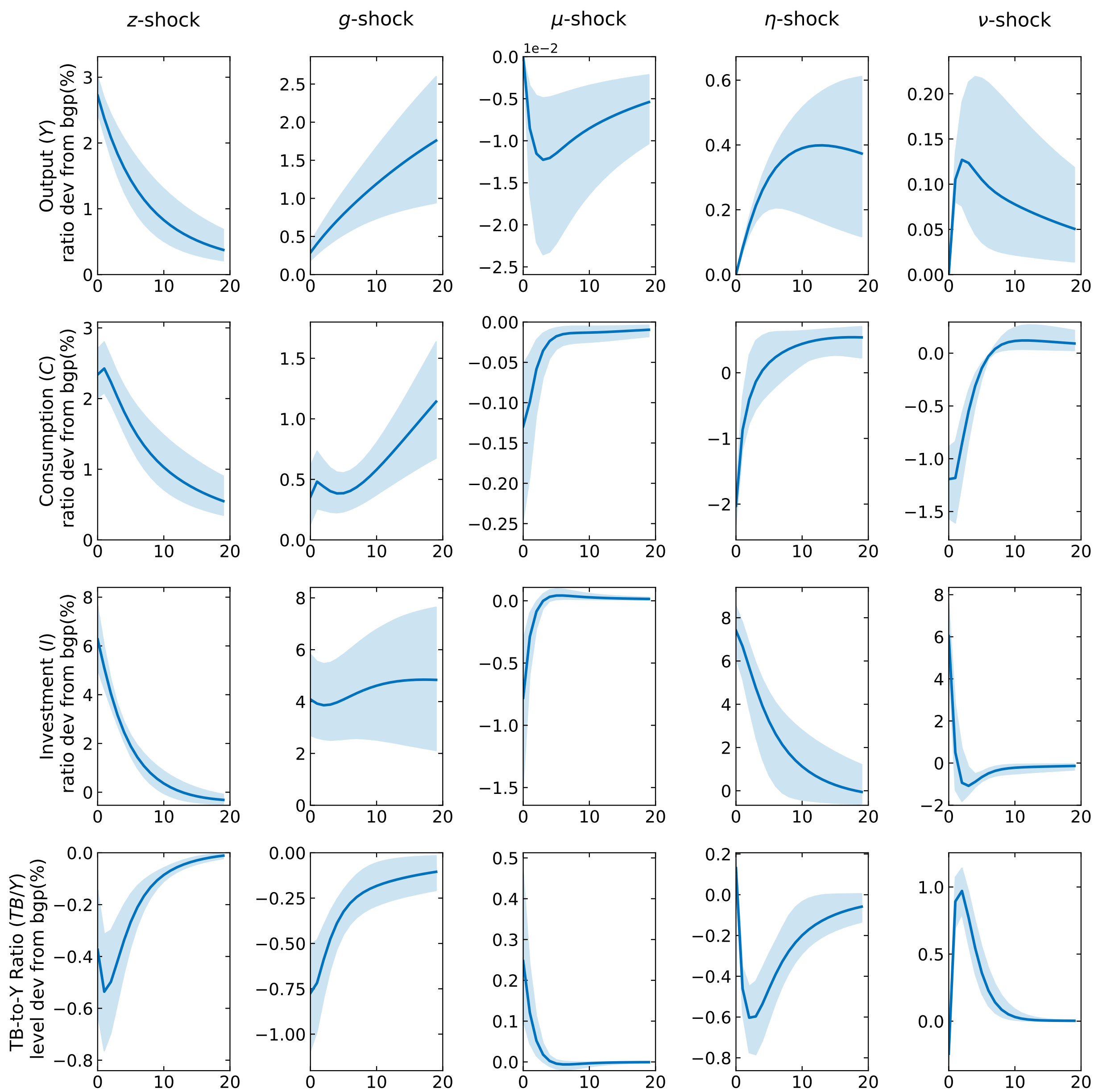


Figure 3.5: Impulse Responses of Output (Y), Consumption (C), Investment (I), and the Trade-Balance-to-Output Ratio (TB/Y) to 1 S.D. Shocks

Notes: In each plot, the blue solid line represents the impulse responses in terms of the deviation from the balanced growth path to a one-standard-deviation shock. The unit on the y-axis in the first three rows is 'ratio dev from bgp(%)', which represents the deviation divided by the value on the balanced growth path, expressed in percent. The unit on the y-axis in the last row is 'level dev from bgp(%)', which represents the deviation itself, expressed in percent. The impulse responses are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure. The shaded area in each plot represents 90% credible bands over the posterior distribution.

tion is substantially lower than one in the data. Provided that stationary productivity shocks play a very large role in generating output growth variations and thus also generate a sizable amount of consumption growth variations that are strongly positively correlated with investment growth variations, the model seeks a shock that can generate a negative correlation between consumption growth and investment growth. As the (2,4)-th, (3,4)-th, (2,5)-th, and (3,5)-th panels of Figure 3.5 suggest, illiquidity shocks and investment shocks can generate a strong negative correlation. Between the two shocks, the model assigns a greater explanatory power for the consumption growth variations to illiquidity shocks.[45]

Illiquidity shocks generate a strong negative correlation between consumption growth and investment growth for the following reasons. When the degree of illiquidity increases, households increase saving, as discussed in 3.3.1. As a result, aggregate consumption decreases while aggregate wealth increases. Since the aggregate wealth is almost entirely saved in illiquid assets, which are firms' shares, the greater amount of illiquid assets should be explained by a greater amount of investment from the perspective of firms.[46] As a consequence, aggregate consumption plunges while investment jumps in response to a positive illiquidity shock.

Table 3.6 also reports the variance decomposition of investment growth and the first difference in the trade-banace-to-output ratio. More than 65 percent of the investment growth variations are explained in equal parts by investment shocks and illiquidity shocks, and stationary productivity shocks also contribute to the variations to a lesser extent. More than half of the variations of the

[45]Between the two shocks that generate a negative correlation between consumption growth and investment growth, illiquidity shocks generate consumption growth variations (relative to investment growth variations) more intensely than investment shocks. In terms of the ratio between the absolute size of the impact effect on consumption and that on investment, illiquidity shocks yield approximately 1/3.5, while investment shocks yield approximately 1/5. Given this feature of the model, if we Bayesian estimate an advanced economy that features low consumption volatility and a low correlation between consumption growth and investment growth in its macro data, a sizable fraction of consumption variations might be captured by investment shocks instead of illiquidity shocks. (As discussed in footnote 38, advanced economies also tend to have a low correlation between consumption growth and investment growth.)

[46]The economic mechanism behind this investment increase is as follows. As a result of households' increased demand for illiquid assets in response to illiquidity shocks, illiquid asset price jumps on impact, and then gradually returns to its value on the balanced growth path. Therefore, illiquid asset return jumps on impact, plunges to a negative value in period 1 (due to the asset price jump in period 0), and then gradually returns to its value on the balanced growth path. Because firms discount profits with illiquid asset returns, and their investment decision in period t is directly affected by the illiquid asset return in period $t + 1$, investment jumps on impact, and gradually returns to its value on the balanced growth path. See impulse responses to illiquidity shocks in Figure C.9 for the graphical illustration of the mechanism.

first difference in the trade-balanace-to-output-ratio are explained by investment shocks, and trend shocks and illiquidity shocks also contribute to the variations to a lesser extent.

3.6.2 Variance Change Decomposition

In subsection 3.6.1, I conduct the variance decomposition for the baseline economy. Once I implement the same variance decomposition for the counterfactual economy calibrated to the U.S. MPCs in section 3.5, I can examine which shock is responsible for the variance change between the two economies. Specifically, I decompose the variance changes from the baseline economy to the counterfactual economy into the changes generated by each shock as follows. Let $V(\Delta \log C_t^{msd})^{Base}$ be the variance of consumption growth and $V(\Delta \log C_t^{msd})^{Base}_{shock}$, $shock \in \{z, g, \mu, \eta, \nu\}$ be the variances decomposed by each shock in the baseline economy. Similarly, let $V(\Delta \log C_t^{msd})^{Counter}$ be the variance of consumption growth, and $V(\Delta \log C_t^{msd})^{Counter}_{shock}$, $shock \in \{z, g, \mu, \eta, \nu\}$ be the variances decomposed by each shock in the counterfactual economy. The variance change (in ratio terms) is decomposed according to the following equation.

$$\frac{V(\Delta \log C_t^{msd})^{Counter} - V(\Delta \log C_t^{msd})^{Base}}{V(\Delta \log C_t^{msd})^{Base}} = \sum_{shock \in \{z,g,\mu,\eta,\nu\}} \frac{V(\Delta \log C_t^{msd})^{Counter}_{shock} - V(\Delta \log C_t^{msd})^{Base}_{shock}}{V(\Delta \log C_t^{msd})^{Base}}.$$

In the same way, I also decompose the variance change of output growth.

Table 3.7 reports the result of this variance change decomposition. As reported in the bottom row of the table, the consumption growth variance decreases by 44.9 percent when Peruvian households are replaced with those exhibiting U.S. MPCs. Of the 44.9 percent decrease in the consumption growth variance, a 20.7 percent decrease comes from the variance change generated by stationary productivity shocks, and a 24.5 percent decrease comes from the variance change generated by illiquidity shocks. This result shows that consumption volatility substantially decreases in the counterfactual economy because both stationary productivity shocks and illiquidity shocks generate substantially less consumption variation.

Table 3.7: Variance Change Decomposition
(from Baseline to Counterfactual)

	$\Delta \log Y_t$	$\Delta \log C_t^{msd}$
stationary productivity shock (z_t)	-0.012	-0.207
	(0.000)	(0.022)
trend shock (g_t)	-0.011	0.053
	(0.008)	(0.027)
interest rate shock (μ_t)	0.000	-0.001
	(0.000)	(0.001)
illiquidity shock (η_t)	-0.001	-0.245
	(0.001)	(0.039)
investment shock (ν_t)	-0.000	-0.049
	(0.000)	(0.020)
variance change (in ratio)	-0.024	-0.449
	(0.008)	(0.042)

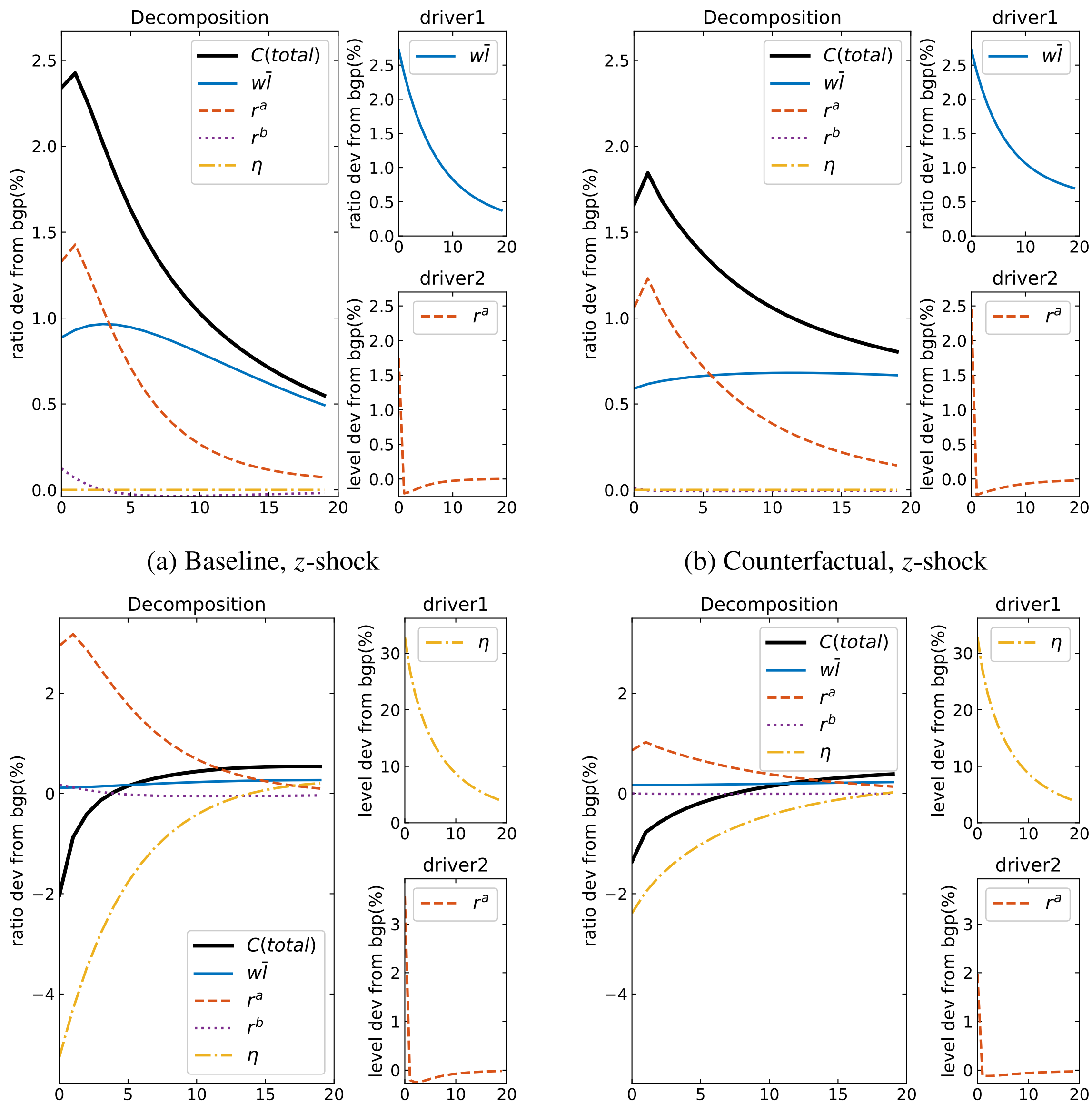
Notes: The last row reports the fraction of [(variance change from the baseline economy to the counterfactual economy) / (variance in the baseline economy)]. The first five rows report the fraction of [(variance change generated by each shock) / (variance in the baseline economy)], in which the denominator is the variance generated by all shocks (*i.e.*, the same denominator used in the fraction reported in the last row.) By construction, the last row is the sum of the first five rows. The statistics are computed under each posterior draw, and their means and standard deviations over the posterior distribution are reported in this table. The numbers in parentheses are the posterior standard deviations.

Table 3.7 also reports the variance change decomposition of output growth. The output growth variance decreases only by 2.5 percent from the baseline economy to the counterfactual economy. This small variance change comes from the variance changes caused by stationary productivity shocks and trend shocks.

3.6.3 Consumption Response Decomposition

Ultimately, consumption is determined by households after they observe the paths of variables that are relevant for their optimization, $\{w_t \bar{l}_t, r_t^a, r_t^b, \eta_t\}_{t=0}^{\infty}$.[47] I name these variables 'drivers'. To understand economic reasons why both stationary productivity shocks and illiquidity shocks generate substantially more consumption variation in the baseline economy than they do in the

[47] In other words, $\{w_t \bar{l}_t, r_t^a, r_t^b, \eta_t\}_{t=0}^{\infty}$ are exogenous variables in the partial equilibrium of the households' optimization, although $\{w_t \bar{l}_t, r_t^a, r_t^b\}_{t=0}^{\infty}$ are endogenous in general equilibrium.



(a) Baseline, z-shock

(b) Counterfactual, z-shock

(c) Baseline, η-shock

(d) Counterfactual, η-shock

Figure 3.6: Decomposition of the Consumption Responses to the z-shock and η-shock

Notes: Panels 3.6a, 3.6b, 3.6c, and 3.6d present the consumption response decomposition with respect to stationary productivity shocks (z) and illiquidity shocks (η) in the baseline economy and the counterfactual economy, respectively. Each panel consists of three subplots, where the large subplot on the left shows the total consumption response as well as decomposed consumption responses to each driver of $\{w_t\bar{l}_t, r_t^a, r_t^b, \eta_t\}_{t=0}^{\infty}$, and the other two small subplots on the right show the equilibrium paths of the two main drivers after the shock. The consumption responses are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure.

counterfactual economy, I decompose households' consumption response to these shocks into the responses to each driver.

Figure 3.6a presents the decomposition of the consumption response with respect to stationary productivity shocks in the baseline economy. This figure consists of three subplots. The largest subplot on the left side labeled ‘Decomposition’ presents the total consumption response to a stationary productivity shock in the baseline economy, as well as the decomposed consumption responses to each driver. This subplot shows that the consumption response is mainly driven by two drivers: $w_t\bar{l}_t$ and r^a_t. The other small subplots on the right side, which are labeled ‘driver1’ and ‘driver2’, plot the equilibrium paths of the two drivers after the shock. The first driver, the labor income per idiosyncratic labor productivity $w_t\bar{l}_t$, jumps on impact and then gradually returns to zero. The second driver, the return rate on illiquid assets r^a_t, also jumps on impact, but then it suddenly falls below zero in period 1 and gradually returns to zero.[48]

Figure 3.6b presents the same consumption response decomposition with respect to stationary productivity shocks but in the counterfactual economy. Three important observations are made from the comparison between Figure 3.6a and Figure 3.6b. First, the total consumption response in the counterfactual economy is substantially weaker than that in the baseline economy. Second, the weaker total consumption response in the counterfactual economy is due to the weaker consumption responses to both $w_t\bar{l}_t$ and r^a_t. Third, the consumption responses to these drivers are weaker in the counterfactual economy despite the fact that the equilibrium paths of the drivers after the shock are similar in the two economies.[49] These observations reveal the first main mechanism through which high-MPC households in the baseline economy contribute to the large consumption volatility: their consumption responds to individual resource fluctuations (mainly generated by the two drivers, $w_t\bar{l}_t$ and r^a_t) far more strongly than the consumption of the counterfactual households exhibiting U.S. MPCs.[50]

---

[48] The jump of the illiquid asset return on impact is due to the jump in the illiquid asset price, which reflects the high capital returns in the future. From period 1 onward, the illiquid asset return r^a_t is equalized with the interest rate in the international financial market r_{t-1} by firms’ optimality condition (3.10).

[49] The initial jump of r^a_t is rather larger in the counterfactual economy, which works against the weaker consumption response.

[50] Households in the baseline economy exhibit stronger consumption responses to individual resource fluctuations than those in the counterfactual economy for the same reason why the former households exhibit higher MPCs than the latter. Households exhibit higher MPCs in the baseline economy because both the degree of consumption smoothing failure of households who face bad idiosyncratic income shocks and the precautionary-saving motive of households who face good idiosyncratic income shocks are substantially stronger, and therefore, a positive transitory income

Figure 3.6c shows the result of the consumption response decomposition with respect to illiquidity shocks in the baseline economy. In response to a positive illiquidity shock, total consumption plunges on impact and then gradually recovers. The plunge in total consumption is mainly driven by the direct effect of illiquidity shocks rather than by indirect effects through other drivers. In the model, the direct effect of illiquidity shocks is realized as follows. When the degree of illiquidity increases, it becomes more expensive for households to liquidate their illiquid assets. For households facing bad idiosyncratic income shocks at the moment of the illiquidity shock, they need to cash out their illiquid assets to smooth their consumption, but it is more difficult to do so because the assets are more illiquid. Therefore, these households fail to smooth consumption more seriously, and as a result, their consumption plunges. For households facing good idiosyncratic income shocks at the moment of the illiquidity shock, they recognize that it will be more difficult to cash out their illiquid assets for a while. Therefore, they prepare themselves for situations in which bad idiosyncratic income shocks are realized in a near future by reducing consumption substantially and accumulating more buffer stocks. In other words, these households' precautionary-saving motive is significantly enhanced.

There is one more noteworthy observation in Figure 3.6c. The illiquid asset return significantly jumps on impact in response to a positive illiquidity shock and generates a substantial positive consumption response.[51] However, the consumption plunge due to the direct effect of the illiquidity shock outweighs the consumption increase in response to illiquid asset returns by a sizable margin. As a result, the total consumption response is negative on impact and over several subsequent periods.

Figure 3.6d presents the same consumption response decomposition with respect to illiquidity shocks but in the counterfactual economy. Two important observations are made from the com-

shock relaxes them substantially more in the baseline economy than in the counterfactual economy. For the same reason, households' resource fluctuations in response to a positive transitory productivity shock relax the degree of consumption smoothing failure and the precautionary-saving motive substantially more in the baseline economy than in the counterfactual economy (despite the fact that households face similar degrees of resource fluctuations in the two economies), and therefore, consumption responds more strongly in the baseline economy.

[51]The initial jump of the illiquid asset return is due to the jump of the illiquid asset price. The illiquid asset price jumps because the stronger degree of illiquidity increases the aggregate adjustment cost χ_t^{agg}, which appears as a part of firms' profit.

parison between Figure 3.6c and Figure 3.6d. First, the total consumption response with respect to illiquidity shocks is significantly weaker in the counterfactual economy. Second, the weaker total consumption response is driven by the weaker direct effect of illiquidity shocks on consumption.[52] In the counterfactual economy, households face a much smaller adjustment cost for illiquid assets. Therefore, the same degree of increase in η_t distorts households' consumption-saving decisions far more mildly in the counterfactual economy than in the baseline economy. These observations reveal the second main channel through which high-MPC households in the baseline economy contribute to aggregate consumption volatility: high-MPC households' consumption plunges when assets become more illiquid because some of them experience aggravated consumption smoothing failure and others come to have an enhanced precautionary-saving motive.

3.7 Inspecting Conventional Theories

In section 3.6, I examine how excess consumption volatility is realized in the model through the consumption-saving behavior of high-MPC households in emerging economies. I find that the main mechanisms of this model are quite different from the existing theories on excess consumption volatility based on representative-agent models. In this section, I examine the extent to which the driving mechanisms of the conventional theories are dampened in my model and discuss the economic reasons.

3.7.1 Strong Consumption Response to Trend Shocks

The first well-accepted theory in the literature is the one developed by Aguiar and Gopinath (2007). They argue that households' consumption responds strongly to trend shocks, and such consumption behavior can generate excess consumption volatility. When a positive trend shock hits the economy, output not only jumps on impact but also grows further in the subsequent periods. Reflecting the future output growth, households' permanent income increases significantly.

[52]The competing force generated by the response to illiquid asset returns is also weaker in the counterfactual economy. However, the direct effect of illiquidity shocks is more significantly weakened, and as a consequence, the total consumption response is weakened in the counterfactual economy.

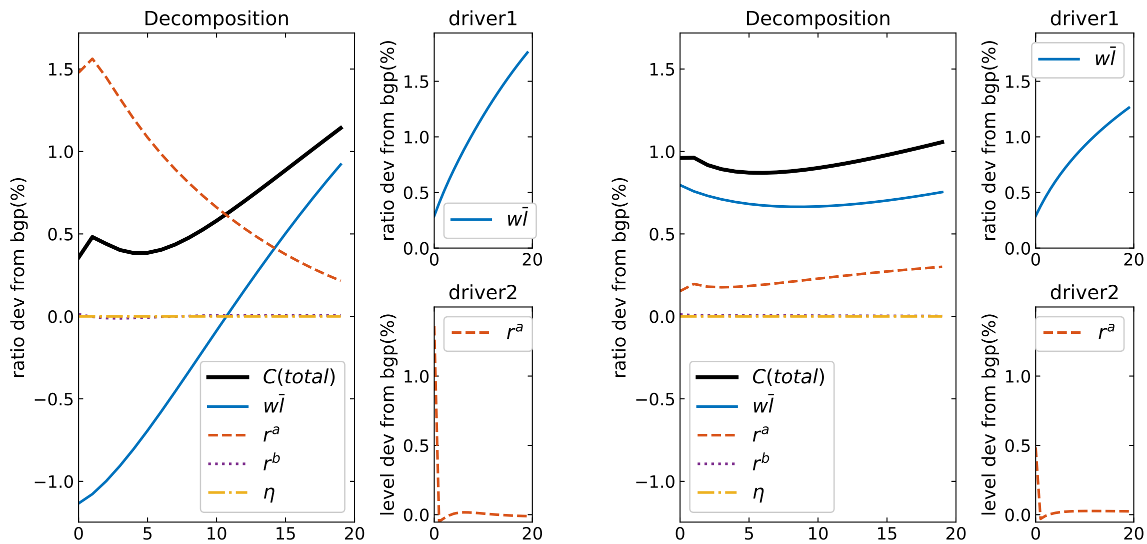
Since representative households follow the PIH, they increase their consumption accordingly. As a result, their consumption jumps far more than their output on impact. Through this mechanism, Aguiar and Gopinath (2007)'s representative-agent model successfully generates excess consumption volatility.

Unlike representative households, the heterogeneous households in my model significantly deviate from the PIH because they face both a large amount of idiosyncratic income risk and financial frictions. In particular, their consumption-saving behavior is different from that of representative households such that Aguiar and Gopinath (2007)'s mechanism cannot be accommodated well.

Figure 3.7a presents the result of the consumption response decomposition with respect to trend shocks in the baseline economy. The total consumption response is mainly driven by consumption responses to two drivers: $w_t\bar{l}_t$ and r_t^a. After a positive trend shock, these drivers move as follows. Driver $w_t\bar{l}_t$ jumps on impact and then increases further in the subsequent periods. Driver r_t^a, on the other hand, jumps substantially on impact, plunges to a negative value in the next period, and then gradually returns to zero.

These observations show how the future output growth in response to a positive trend shock enters into households' budget constraints through two channels. First, the future growth of aggregate labor income enters into the households' budget constraints as the future growth of labor income per idiosyncratic labor productivity ($w_t\bar{l}_t$). Second, the future growth of aggregate capital income is reflected in the asset price of illiquid assets and thus enters into the households' budget constraints as a jump in illiquid asset returns (r_t^a) on impact. Both channels make heterogeneous households' idiosyncratic income profiles either more increasing or less decreasing and thus create a positive wealth effect. Households would want to increase their consumption in response to this positive wealth effect.

As the large panel on the left of Figure 3.7a shows, households exhibit a strong positive consumption response to driver r_t^a, reflecting the positive wealth effect. However, households substantially decrease their consumption in response to driver $w_t\bar{l}_t$, despite the positive wealth effect it creates. The economic reason for this consumption plunge is an enhanced precautionary-saving



(a) Baseline, g-shock

(b) Counterfactual, g-shock

Figure 3.7: Decomposition of the Consumption Responses to the g-shock

Notes: Panels 3.7a and 3.7b present the consumption response decomposition with respect to trend shocks (g) in the baseline economy and the counterfactual economy, respectively. Each panel consists of three subplots, where the large subplot on the left shows the total consumption response as well as decomposed consumption responses to each driver of $\{w_t\bar{l}_t, r_t^a, r_t^b, \eta_t\}_{t=0}^{\infty}$, and the other two small subplots on the right show the equilibrium paths of the two main drivers after the shock. The consumption responses are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure.

motive. In the model, the future growth of $w_t\bar{l}_t$ means that idiosyncratic income risk will grow in the future as the variance of $w_t\bar{l}_t e_{i,t}$ increases. Households prepare themselves for this greater income risk by accumulating additional buffer stocks. Since households allocate most of their savings to illiquid assets, they have to pay a large adjustment cost when they need to cash out illiquid assets by facing bad idiosyncratic income shocks. In this environment, the amount of additional buffer stocks that households accumulate in response to increased income risk is also large. Because of this greatly enhanced precautionary-saving motive, households substantially decrease their consumption. In terms of the total consumption response, this enhanced precautionary-saving motive offsets most of the positive wealth effect, and as a consequence, the total consumption response is significantly subdued.

Figure 3.7b presents the same consumption response decomposition with respect to trend shocks but in the counterfactual economy. Two important observations are made from the comparison between Figure 3.7a and Figure 3.7b. First, the total consumption response to a trend shock in the counterfactual economy is substantially stronger than the response in the baseline economy on impact. Second, the stronger initial jump of total consumption in the counterfactual economy is driven by the strong and positive consumption response to $w_t\bar{l}_t$, which is in the opposite direction from the strong and negative response to it in the baseline economy. The sign of the consumption response to driver $w_t\bar{l}_t$ is flipped because the precautionary-saving motive is enhanced far less intensely in the counterfactual economy (since households face much smaller illiquid asset adjustment costs). As a consequence, the positive wealth effect dominates the enhanced precautionary-saving motive in the counterfactual economy.[53]

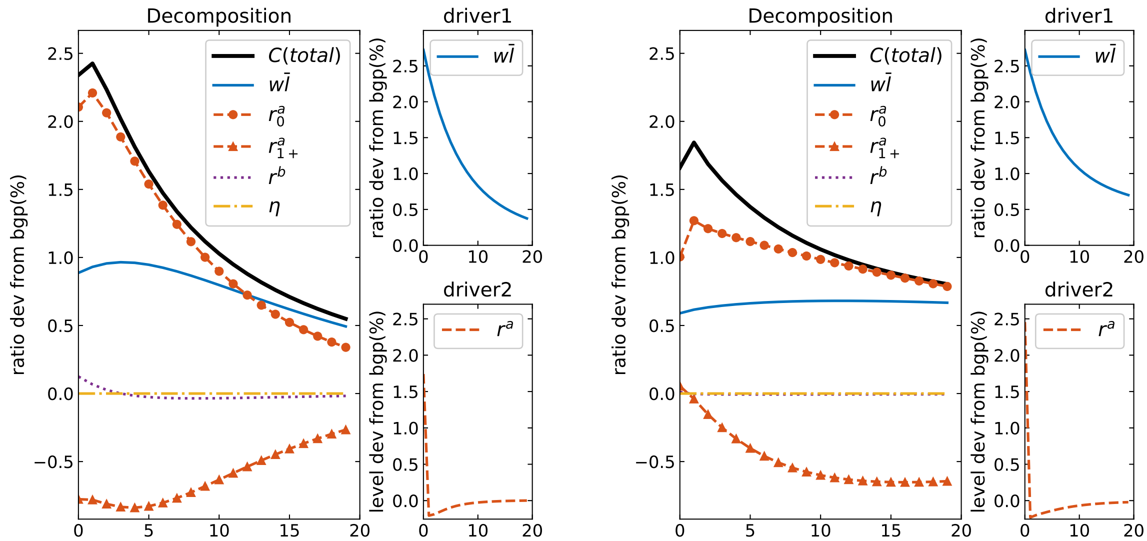
The observations from Figure 3.7a and Figure 3.7b show that Aguiar and Gopinath (2007)'s mechanism does not drive the consumption response in the baseline economy because households' consumption-saving behavior is very different from that of representative households, particularly due to the precautionary-saving motive.

3.7.2 Intertemporal Substitution in Response to Interest Rate Variations

The second well-accepted theory in the literature is the one developed by Neumeyer and Perri (2005). Emerging economies face volatile interest rate variations, induced either by domestic economic conditions or purely external factors. Neumeyer and Perri (2005) argue that households intertemporally substitute their consumption in response to interest rate variations, and such consumption behavior can generate the excess consumption volatility of emerging economies.

In my model, the interest rates in the international financial market are determined by equation (3.11). Provided that interest rate shocks (μ_t) and trend shocks (g_t) both have small volatility as a result of the Bayesian estimation, a large fraction of interest rate fluctuations are induced by

[53] The positive consumption response to driver r_t^a is also weakened in the counterfactual economy. There are two economic reasons. First, the initial jump of r_t^a is far weaker in the counterfactual economy because the aggregate adjustment cost for illiquid assets χ_t^{agg} increases much less than in the baseline economy. Second, even if we control for the dynamics of driver r_t^a, households in the counterfactual economy respond much more mildly than those in the baseline economy because of the MPC difference. Despite all the reasons for the weakened consumption response to driver r_t^a, the total consumption response is still substantially stronger in the counterfactual economy than in the baseline economy because the effect of the flipped consumption response to driver $w_t\bar{l}_t$ dominates.



(a) Baseline, z-shock

(b) Counterfactual, z-shock

Figure 3.8: Decomposition of the Consumption Responses to the z-shock, $\{r_0^a\}$ and $\{r_t^a\}_{t\geq 1}$ split

Notes: Panels 3.8a and 3.8b present the same consumption response decomposition with respect to stationary productivity shocks (z) as panels 3.6a and 3.6b except for one difference: the consumption response to $\{r_t^a\}_{t\geq 0}$ is further decomposed into the responses to $\{r_0^a\}$ and $\{r_t^a\}_{t\geq 1}$. The consumption responses are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure.

stationary productivity shocks.

To see how the stationary-productivity-shock-induced interest rate fluctuations affect households' consumption, in Figure 3.8a, I report the same consumption response decomposition with respect to stationary productivity shocks as in Figure 3.6a except for one difference: the consumption response to driver r^a is further decomposed into the consumption responses to r_0^a and to $r_t^a,\ t \geq 1$. Note that $r_t^a = r_{t-1},\ t \geq 1$, as equation (3.10) dictates. Importantly, only $r_t^a,\ t \geq 1$ (but not r_0^a) can generate the intertemporal substitution of consumption in households' optimization. Specifically, the consumption response to r_0^a purely comes from a positive wealth effect, while the consumption response to $\{r_t^a\}_{t\geq 1}$ comes from both a negative wealth effect and a positive intertemporal substitution effect. As Figure 3.8a shows, the consumption response to $\{r_t^a\}_{t\geq 1}$ is negative on impact and in the subsequent periods, meaning that the negative wealth effect dominates the positive intertemporal substitution effect. Regarding the total consumption response, however, the positive wealth effect in the consumption response to r_0^a dominates the negative wealth effect in the consumption response to $r_t^a,\ t \geq 1$.

Figure 3.8b plots the same consumption response decomposition as Figure 3.8a but in the counterfactual economy. In the consumption response to $r_t^a,\ t \geq 1$, the positive intertemporal substitution effect is no longer dominated by the negative wealth effect on impact in the counterfactual economy. This change occurs because i) the intertemporal substitution effect recovers as the illiquid asset adjustment cost decreases, and ii) the wealth effect is weakened due to the lower MPCs. Despite this less negative consumption response to $r_t^a,\ t \geq 1$, however, the total consumption response is significantly weaker in the counterfactual economy because the positive wealth effect in the consumption response to r_0^a is substantially subdued due to the lower MPCs.

The observations from Figure 3.8a and Figure 3.8b show that unlike representative-agent models, the intertemporal substitution of consumption does not drive the consumption response in the baseline economy of my model. The economic reasons why this mechanism is dampened in my model are as follows. First, unlike representative households whose consumption is solely determined by their lifetime wealth and the degree of intertemporal substitution, the consumption-saving behavior of households in my model is also greatly affected by the precautionary-saving motive, as we see in the previous discussions. Second, the fact that households in my model allocate most of their savings to illiquid assets makes it even more difficult for them to shift resources across time.

3.8 Conclusion

This chapter studies the role of high-MPC households in emerging market business cycles through the lens of a heterogeneous-agent small open economy model. To this end, I discipline the model using both micro moments (MPC estimates from micro data) and macro moments (covariances of macro data) from Peru. Through the counterfactual experiment in which I replace Peruvian households with those exhibiting U.S. MPCs, which are substantially lower than the Peruvian MPCs, I find that the high-MPC households play a key role in generating the phenomenon of excess consumption volatility. Three decomposition exercises (variance decomposition, variance change decomposition, and consumption response decomposition) reveal that high-MPC households contribute to the large aggregate consumption volatility of emerging economies through i) their strong consumption response to individual resource fluctuations and ii) large consumption reduction when illiquid assets become more illiquid (because of some households' aggravated consumption smoothing failure and other households' enhanced precautionary saving). The driving mechanisms in conventional theories do not play an important role in my model because the high-MPC households, who significantly deviate from the PIH, cannot accommodate them well.

The scope of this chapter is confined to the business cycle implications of high MPC households in emerging economies. However, it is likely that the presence of high-MPC households in emerging economies has many other interesting macroeconomic implications, as previous studies focused on developed economies suggest. Revisiting key macroeconomic issues of emerging economies – such as aggregate dynamics during financial crises and the transmission mechanisms of macroeconomic policies – through the lens of a heterogeneous-agent model in which households exhibit MPCs as high as the empirical estimates from micro data would be an important future avenue in the field of international macroeconomics.

References

Aguiar, M., M. Bils, and C. Boar (2019). Who Are the Hand-to-Mouth? Working Paper.

Aguiar, M. and G. Gopinath (2007). Emerging Market Business Cycles: The Cycle is the Trend. *Journal of Political Economy 115*(1), 69–102.

Ahn, S., G. Kaplan, B. Moll, T. Winberry, and C. Wolf (2018). When Inequality Matters for Macro and Macro Matters for Inequality. *NBER Macroeconomics Annual 32*(1), 1–75.

Aiyagari, S. R. (1994). Uninsured Idiosyncratic Risk and Aggregate Saving. *The Quarterly Journal of Economics 109*(3), 659–684.

Andrews, D. W. (1993). Tests for Parameter Instability and Structural Change with Unknown Change Point. *Econometrica: Journal of the Econometric Society*, 821–856.

Arellano, C. (2008). Default Risk and Income Fluctuations in Emerging Economies. *American Economic Review 98*(3), 690–712.

Atkeson, A. and L. E. Ohanian (2001). Are Phillips Curves Useful for Forecasting Inflation? *Federal Reserve Bank of Minneapolis Quarterly Review 25*(1), 2–11.

Attanasio, O. P. and G. Weber (1995). Is Consumption Growth Consistent with Intertemporal Optimization? Evidence from the Consumer Expenditure Survey. *Journal of Political Economy 103*(6), 1121–1157.

Auclert, A. (2019). Monetary Policy and the Redistribution Channel. *American Economic Review 109*(6), 2333–67.

Auclert, A., B. Bardóczy, M. Rognlie, and L. Straub (2019). Using the Sequence-Space Jacobian to Solve and Estimate Heterogeneous-Agent Models. National Bureau of Economic Research Working Paper No. 26123.

Auclert, A. and M. Rognlie (2017). A Note on Multipliers in NK Models with GHH Preferences. Report, Stanford.[269].

Auclert, A., M. Rognlie, and L. Straub (2018). The Intertemporal Keynesian Cross. National Bureau of Economic Research Working Paper No. 25020.

Auclert, A., M. Rognlie, and L. Straub (2020). Micro Jumps, Macro Humps: Monetary Policy and Business Cycles in an Estimated HANK Model. National Bureau of Economic Research Working Paper No. 26647.

Bayer, C., B. Born, and R. Luetticke (2020). Shocks, Frictions, and Inequality in US Business Cycles. CEPR Discussion Paper No. 14364.

Bayer, C. and R. Luetticke (2020). Solving Heterogeneous Agent Models in Discrete Time with Many Idiosyncratic States by Perturbation Methods. *Quantitative Economics*. Forthcoming.

Bayer, C., R. Luetticke, L. Pham-Dao, and V. Tjaden (2019). Precautionary Savings, Illiquid Assets, and the Aggregate Consequences of Shocks to Household Income Risk. *Econometrica 87*(1), 255–290.

Bianchi, J. (2011). Overborrowing and Systemic Externalities in the Business Cycle. *American Economic Review 101*(7), 3400–3426.

Blundell, R., L. Pistaferri, and I. Preston (2008). Consumption Inequality and Partial Insurance. *American Economic Review 98*(5), 1887–1921.

Boppart, T., P. Krusell, and K. Mitman (2018). Exploiting MIT Shocks in Heterogeneous-Agent Economies: the Impulse Response as a Numerical Derivative. *Journal of Economic Dynamics and Control 89*, 68–92.

Caner, M. and B. E. Hansen (2004). Instrumental Variable Estimation of a Threshold Model. *Econometric Theory 20*(5), 813–843.

Carroll, C. D. (2006). The Method of Endogenous Gridpoints for Solving Dynamic Stochastic Optimization Problems. *Economics Letters 91*(3), 312–320.

Chang, R. and A. Fernández (2013). On the Sources of Aggregate Fluctuations in Emerging Economies. *International Economic Review 54*(4), 1265–1293.

Crawley, E. (2019). In Search of Lost Time Aggregation. Finance and Economics Discussion Series 2019-075. Washington: Board of Governors of the Federal Reserve System, `https://doi.org/10.17016/FEDS.2019.075`.

Cugat, G. (2019). Emerging Markets, Household Heterogeneity, and Exchange Rate Policy. Society for Economic Dynamics 2019 Meeting Paper No. 526.

Davies, R. B. (1977). Hypothesis Testing When a Nuisance Parameter Is Present Only Under the Alternative. *Biometrika 64*(2), 247–254.

Davies, R. B. (1987). Hypothesis Testing When a Nuisance Parameter Is Present Only Under the Alternative. *Biometrika 74*(1), 33–43.

De Ferra, S., K. Mitman, and F. Romei (2020). Household Heterogeneity and the Transmission of Foreign Shocks. *Journal of International Economics 124*, 103–303.

Demirguc-Kunt, A., L. Klapper, D. Singer, S. Ansar, and J. Hess (2018). *The Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution*. The World Bank.

Demirguc-Kunt, A., L. Klapper, D. Singer, and P. Van Oudheusden (2015). *The Global Findex Database 2014: Measuring Financial Inclusion around the World*. The World Bank.

Diaz-Gimenez, J., V. Quadrini, and J.-V. Rios-Rull (1997). Dimensions of Inequality: Facts on the US Distribution of Earnings, Income and Wealth. *Federal Reserve Bank of Minneapolis Quarterly Review 21*(2), 3–21.

Egger, D., J. Haushofer, E. Miguel, P. Niehaus, and M. W. Walker (2019). General Equilibrium Effects of Cash Transfers: Experimental Evidence from Kenya.

Fagereng, A., L. Guiso, D. Malacrino, and L. Pistaferri (2020). Heterogeneity and Persistence in Returns to Wealth. *Econometrica 88*(1), 115–170.

Feenstra, R. C., R. Inklaar, and M. P. Timmer (2015). The Next Generation of the Penn World Table. *American Economic Review 105*(10), 3150–82.

Fernandez-Villaverde, J., P. Guerron-Quintana, J. F. Rubio-Ramirez, and M. Uribe (2011). Risk Matters: The Real Effects of Volatility Shocks. *American Economic Review 101*(6), 2530–61.

Floden, M. and J. Lindé (2001). Idiosyncratic Risk in the United States and Sweden: Is There a Role for Government Insurance? *Review of Economic Dynamics 4*(2), 406–437.

Garcia-Cicco, J., R. Pancrazi, and M. Uribe (2010). Real Business Cycles in Emerging Countries? *American Economic Review 100*(5), 2510–31.

Geary, R. C. (1950). A Note on "A Constant-Utility Index of the Cost of Living". *The Review of Economic Studies 18*(1), 65–66.

Greenwood, J., Z. Hercowitz, and G. W. Huffman (1988). Investment, Capacity Utilization, and the Real Business Cycle. *American Economic Review*, 402–417.

Guntin, R., P. Ottonello, and D. Perez (2020). The Micro Anatomy of Macro Consumption Adjustments. National Bureau of Economic Research Working Paper No. 27917.

Guvenen, F. and A. A. Smith (2014). Inferring Labor Income Risk and Partial Insurance from Economic Choices. *Econometrica 82*(6), 2085–2129.

Haushofer, J. and J. Shapiro (2016). The Short-term Impact of Unconditional Cash Transfers to the Poor: Experimental Evidence from Kenya. *The Quarterly Journal of Economics 131*(4), 1973–2042.

Herbst, E. P. and F. Schorfheide (2015). *Bayesian Estimation of DSGE Models*. Princeton University Press.

Instituto Nacional de Estadística e Informática (2004-2016). Encuesta Nacional de Hogares. `http://iinei.inei.gob.pe/microdatos/`.

Instituto Nacional de Estadística e Informática (2004, 2007, 2010-2016). Encuesta Nacional de Hogares - Manual del Encuestador. `http://iinei.inei.gob.pe/microdatos/`.

Instituto Nacional de Estadística e Informática (2009-2016). Encuesta Nacional de Hogares - Calidad de la Encuesta. `http://iinei.inei.gob.pe/microdatos/`.

Instituto Nacional de Estadística e Informática (n.d.). Metodología de Cálculo del Producto Bruto Interno Anual. https://www.inei.gob.pe/media/MenuRecursivo/metodologias/pbi02.pdf.

Iyer, T. (2015). Inflation Targeting for India?: The Implications of Limited Asset Market Participation. Working Paper.

Jappelli, T. and L. Pistaferri (2014). Fiscal Policy and MPC Heterogeneity. *American Economic Journal: Macroeconomics 6*(4), 107–136.

Johnson, D. S., J. A. Parker, and N. S. Souleles (2006). Household Expenditure and the Income Tax Rebates of 2001. *American Economic Review 96*(5), 1589–1610.

Justiniano, A., G. E. Primiceri, and A. Tambalotti (2010). Investment Shocks and Business Cycles. *Journal of Monetary Economics 57*(2), 132–145.

Kaplan, G., B. Moll, and G. L. Violante (2018). Monetary Policy According to HANK. *American Economic Review 108*(3), 697–743.

Kaplan, G. and G. L. Violante (2010). How Much Consumption Insurance beyond Self-Insurance? *American Economic Journal: Macroeconomics 2*(4), 53–87.

Kaplan, G., G. L. Violante, and J. Weidner (2014a). Replication Data for: "The Wealthy Hand-to-Mouth". https://gregkaplan.me/academic-publications.

Kaplan, G., G. L. Violante, and J. Weidner (2014b). The Wealthy Hand-to-Mouth. *Brookings Papers On Economic Activity*, 77–138.

Kocherlakota, N. and L. Pistaferri (2009). Asset Pricing Implications of Pareto Optimality with Private Information. *Journal of Political Economy 117*(3), 555–590.

Krueger, D., K. Mitman, and F. Perri (2016). Macroeconomics and Household Heterogeneity. In *Handbook of Macroeconomics*, Volume 2, pp. 843–921. Elsevier.

Krueger, D. and F. Perri (2006). Does Income Inequality Lead to Consumption Inequality? Evidence and Theory. *The Review of Economic Studies 73*(1), 163–193.

McKay, A., E. Nakamura, and J. Steinsson (2016). The Power of Forward Guidance Revisited. *American Economic Review 106*(10), 3133–58.

Mendoza, E. G. (2010). Sudden Stops, Financial Crises, and Leverage. *American Economic Review 100*(5), 1941–66.

Mendoza, E. G. and V. Z. Yue (2012). A General Equilibrium Model of Sovereign Default and Business Cycles. *The Quarterly Journal of Economics 127*(2), 889–946.

Milesi-Ferretti, G. M. and P. R. Lane (2017). International Financial Integration in the Aftermath of the Global Financial Crisis. Working Paper 115, International Monetary Fund.

Neumeyer, P. A. and F. Perri (2005). Business Cycles in Emerging Economies: the Role of Interest Rates. *Journal of Monetary Economics 52*(2), 345–380.

Oh, H. and R. Reis (2012). Targeted Transfers and the Fiscal Response to the Great Recession. *Journal of Monetary Economics 59*, S50–S64.

Parker, J. A., N. S. Souleles, D. S. Johnson, and R. McClelland (2013). Consumer Spending and the Economic Stimulus Payments of 2008. *American Economic Review 103*(6), 2530–2553.

Paxson, C. H. (1992). Using Weather Variability to Estimate the Response of Savings to Transitory Income in Thailand. *The American Economic Review*, 15–33.

Reiter, M. (2009). Solving Heterogeneous-Agent Models by Projection and Perturbation. *Journal of Economic Dynamics and Control 33*(3), 649–665.

Stone, R. (1954). Linear Expenditure Systems and Demand Analysis: an Application to the Pattern of British Demand. *The Economic Journal 64*(255), 511–527.

Sunel, E. (2018). Welfare Consequences of Gradual Disinflation in Emerging Economies. *Journal of Money, Credit and Banking 50*(4), 705–755.

Uribe, M. and S. Schmitt-Grohé (2017). *Open Economy Macroeconomics*. Princeton University Press.

Uribe, M. and V. Z. Yue (2006). Country Spreads and Emerging Countries: Who Drives Whom? *Journal of International Economics 69*(1), 6–36.

Winberry, T. (2018). A Method for Solving and Estimating Heterogeneous Agent Macro Models. *Quantitative Economics 9*(3), 1123–1151.

Zeldes, S. P. (1989). Consumption and Liquidity Constraints: an Empirical Investigation. *Journal of Political Economy 97*(2), 305–346.

Appendix A: Appendix to Chapter 1

A.1 Derivation of the Consumption Growth Function

In this section, I derive the consumption growth function (1.6) from the optimality conditions of the underlying model discussed in subsection 1.2.1. The derivation is nearly identical to that of Blundell et al. (2008), except for the part that deals with liquidity constraints, which are absent in their underlying model.

Let $\hat{\mu}_{i,t+j} := \mu_{i,t+j}/(e^{(Z'_{i,t+j}\varphi^p_{t+j})}C^{-\sigma}_{i,t+j})$ be the shadow cost of liquidity constraint in terms of consumption goods in period $t+j$. Equation (1.2) can be re-written as

$$\begin{aligned}\exp\big(-\sigma\log C_{i,t+j} + Z'_{i,t+j}\varphi^p_{t+j} - \log\beta - \log(1+r_{t+j}) + \log(1-\hat{\mu}_{i,t+j})\big)\\ = E_{t+j}\big[\exp(-\sigma\log C_{i,t+j+1} + Z'_{i,t+j+1}\varphi^p_{t+j+1})\big].\end{aligned} \tag{A.1}$$

By log-linearizing the marginal utility in period $t+j+1$,

$$\exp(-\sigma\log C_{i,t+j+1} + Z'_{i,t+j+1}\varphi^p_{t+j+1}),$$

around its expected value in period $t+j$,

$$\exp\big(-\sigma\log C_{i,t+j} + Z'_{i,t+j}\varphi^p_{t+j} - \log\beta - \log(1+r_{t+j}) + \log(1-\hat{\mu}_{i,t+j})\big)$$

in equation (A.1)[1], we can obtain

$$\Delta \log C_{i,t+j+1} = \frac{1}{\sigma}\Delta(Z'_{i,t+j+1}\varphi^{p}_{t+j+1}) + \frac{1}{\sigma}\log\beta + \frac{1}{\sigma}\log(1+r_{t+j}) - \frac{1}{\sigma}\log(1-\hat{\mu}_{i,t+j}) + \eta^{c}_{i,t+j+1} \quad \text{(A.2)}$$

in which $\eta^{c}_{i,t+j+1}$ is an expectation error satisfying $E_{t+j}\eta^{c}_{i,t+j+1} = 0$.

Note that

$$E_t \log C_{i,t+j} - E_{t-1}\log C_{i,t+j} = E_t\big(\sum_{s=0}^{j}\Delta\log C_{i,t+s}\big) - E_{t-1}\big(\sum_{s=0}^{j}\Delta\log C_{i,t+s}\big). \quad \text{(A.3)}$$

From equation (A.2), we have

$$\begin{aligned}\sum_{s=0}^{j}\Delta\log C_{i,t+s} =& \frac{1}{\sigma}(Z'_{i,t+j}\varphi^{p}_{t+j} - Z'_{i,t-1}\varphi^{p}_{t-1}) + \frac{j+1}{\sigma}\log\beta + \frac{1}{\sigma}\sum_{s=0}^{j}\log(1+r_{t+s-1}) \\ & - \frac{1}{\sigma}\sum_{s=0}^{j}\log(1-\hat{\mu}_{i,t+s-1}) + \sum_{s=0}^{j}\eta^{c}_{i,t+s}.\end{aligned} \quad \text{(A.4)}$$

By substituting equation (A.4) into equation (A.3), we can obtain

$$\begin{aligned}E_t\log C_{i,t+j} - E_{t-1}\log C_{i,t+j} =& \frac{1}{\sigma}(E_t Z'_{i,t+j}\varphi^{p}_{t+j} - E_{t-1}Z'_{i,t+j}\varphi^{p}_{t+j}) \\ & - \frac{1}{\sigma}(E_t\log Q_{t,t+j} - E_{t-1}\log Q_{t,t+j}) \\ & - \frac{1}{\sigma}\sum_{s=0}^{j}\big(E_t\log(1-\hat{\mu}_{i,t+s-1}) - E_{t-1}\log(1-\hat{\mu}_{i,t+s-1})\big) + \eta^{c}_{i,t}, \quad 0 \le j \le J_{i,t}.\end{aligned} \quad \text{(A.5)}$$

The intertemporal budget constraint (1.5) in period t is

$$\sum_{j=0}^{J_{i,t}} Q_{t,t+j}C_{i,t+j} = \sum_{j=0}^{J_{i,t}} Q_{t,t+j}Y_{i,t+j} + (1+r_{t-1})A_{i,t-1}, \quad \text{(A.6)}$$

[1] In other words, first-order-Taylor-approximate

$$-\sigma\log C_{i,t+j+1} + Z'_{i,t+j+1}\varphi^{p}_{t+j+1}$$

around

$$-\sigma\log C_{i,t+j} + Z'_{i,t+j}\varphi^{p}_{t+j} - \log\beta - \log(1+r_{t+j}) + \log(1-\hat{\mu}_{i,t+j}).$$

which can be re-written as

$$
\begin{aligned}
&\log\left(\sum_{j=0}^{J_{i,t}} \exp\left(\log Q_{t,t+j}C_{i,t+j}\right)\right) \\
&= \log\left(\sum_{j=0}^{J_{i,t}} \exp\left(\log Q_{t,t+j}Y_{i,t+j}\right) + (1+r_{t-1})\exp\left(\log A_{i,t-1}\right)\right).
\end{aligned}
\tag{A.7}
$$

The first-order approximation of the intertemporal budget constraint is conducted around the lifetime path of individual variables predicted by the history of observable characteristics and aggregate states. I choose this path as the path around which the variables are log-linearized because i) I want the coefficients evaluated on the path to be independent of individual income shocks $\epsilon_{i,t}$ and $\zeta_{i,t}$, and ii) I want the path to be the most accurate prediction among those satisfying the first condition.

Let $\hat{E}_t[\cdot]$ be the expectation conditional on the history of observable characteristics and aggregate shocks (or, equivalently, the history of all exogenous variables except individual households' idiosyncratic income shocks, $(\epsilon_{t-s})_{s\geq 0}$ and $(\zeta_{t-s})_{s\geq 0}$). In other words,

$$
\hat{E}_t[x_{i,t+j}] := E\left[x_{i,t+j}|(Z_{i,t-s})_{s\geq 0},\ (\varphi^{p1}_{t-s})_{s\geq 0},\ (\varphi^{y1}_{t-s})_{s\geq 0},\ (r_{t-s})_{s\geq 0}\right]
$$

for any stochastic time series $(x_{i,t})_t$.

By taking $\hat{E}_{t-1}[\cdot]$ on both sides of equation (A.6), we can obtain

$$
\sum_{j=0}^{J_{i,t}} \hat{E}_{t-1}[Q_{t,t+j}C_{i,t+j}] = \sum_{j=0}^{J_{i,t}} \hat{E}_{t-1}[Q_{t,t+j}Y_{i,t+j}] + (1+r_{t-1})\hat{E}_{t-1}[A_{i,t-1}].
$$

By log-linearizing

$$
\left\{(Q_{t,t+j}C_{i,t+j})_{0\leq j\leq J_{i,t}},\ (Q_{t,t+j}Y_{i,t+j})_{0\leq j\leq J_{i,t}},\ A_{i,t-1}\right\}
$$

around

$$\left\{\left(\hat{E}_{t-1}[Q_{t,t+j}C_{i,t+j}]\right)_{0\leq j\leq J_{i,t}},\ \left(\hat{E}_{t-1}[Q_{t,t+j}Y_{i,t+j}]\right)_{0\leq j\leq J_{i,t}},\ \hat{E}_{t-1}[A_{i,t-1}]\right\}$$

in equation (A.6)[2], we can obtain

$$\begin{aligned}\sum_{j=0}^{J_{i,t}}\theta_{i,t,t+j}(\log Q_{t,t+j}C_{i,t+j} - \log\hat{E}_{t-1}[Q_{t,t+j}C_{i,t+j}])\\ = \pi_{i,t}\sum_{j=0}^{J_{i,t}}\gamma_{i,t,t+j}(\log Q_{t,t+j}Y_{i,t+j} - \log\hat{E}_{t-1}[Q_{t,t+j}Y_{i,t+j}])\\ + (1-\pi_{i,t})(\log A_{i,t-1} - \log\hat{E}_{t-1}[A_{i,t-1}])\end{aligned} \tag{A.8}$$

in which

$$\theta_{i,t,t+j} = \frac{\hat{E}_{t-1}[Q_{t,t+j}C_{i,t+j}]}{\sum_{j'=0}^{J_{i,t}}\hat{E}_{t-1}[Q_{t,t+j'}C_{i,t+j'}]}, 0\leq j\leq J_{i,t},$$

$$\pi_{i,t} = \frac{\sum_{j'=0}^{J_{i,t}}\hat{E}_{t-1}[Q_{t,t+j'}Y_{i,t+j'}]}{\sum_{j'=0}^{J_{i,t}}\hat{E}_{t-1}[Q_{t,t+j'}Y_{i,t+j'}] + (1+r_{t-1})\hat{E}_{t-1}A_{i,t-1}},\ \text{and}$$

$$\gamma_{i,t,t+j} = \frac{\hat{E}_{t-1}[Q_{t,t+j}Y_{i,t+j}]}{\sum_{j'=0}^{J_{i,t}}\hat{E}_{t-1}[Q_{t,t+j'}Y_{i,t+j'}]}, 0\leq j\leq J_{i,t}.$$

Note that

$$\sum_{j=0}^{J_{i,t}}\theta_{i,t,t+j} = \sum_{j=0}^{J_{i,t}}\gamma_{i,t,t+j} = 1.$$

Moreover, $(\theta_{i,t,t+j},\pi_{i,t},\gamma_{i,t,t+j})_{t,0\leq j\leq J_{i,t}}$ are independent of the household's idiosyncratic income shocks $(\zeta_{i,t},\epsilon_{i,t})_t$ because they are functions of $(Z_{i,t-s})_{s\geq 0}$, $(\varphi^{p1}_{t-s})_{s\geq 0}$, $(\varphi^{y1}_{t-s})_{s\geq 0}$, and $(r_{t-s})_{s\geq 0}$.

By taking the first difference in expectations without hat (*i.e.*, $E_t[\cdot] - E_{t-1}[\cdot]$) on both sides of

[2] In other words, first-order-Taylor-approximate

$$\left\{(\log Q_{t,t+j}C_{i,t+j})_{0\leq j\leq J_{i,t}}, (\log Q_{t,t+j}Y_{i,t+j})_{0\leq j\leq J_{i,t}}, \log A_{i,t-1}\right\}$$

around

$$\left\{\left(\log\hat{E}_{t-1}[Q_{t,t+j}C_{i,t+j}]\right)_{0\leq j\leq J_{i,t}},\ \left(\log\hat{E}_{t-1}[Q_{t,t+j}Y_{i,t+j}]\right)_{0\leq j\leq J_{i,t}},\ \log\hat{E}_{t-1}[A_{i,t-1}]\right\}$$

in equation (A.7).

equation (A.8), we can obtain

$$\sum_{j=0}^{J_{i,t}} \theta_{i,t,t+j}(E_t \log Q_{t,t+j}C_{i,t+j} - E_{t-1}\log Q_{t,t+j}C_{i,t+j})$$
$$= \pi_{i,t}\sum_{j=0}^{J_{i,t}} \gamma_{i,t,t+j}(E_t \log Q_{t,t+j}Y_{i,t+j} - E_{t-1}\log Q_{t,t+j}Y_{i,t+j})$$

or, equivalently,

$$\begin{aligned}
&\sum_{j=0}^{J_{i,t}}\theta_{i,t,t+j}(E_t \log C_{i,t+j} - E_{t-1}\log C_{i,t+j})\\
&\quad = \sum_{j=0}^{J_{i,t}}(\pi_{i,t}\gamma_{i,t,t+j} - \theta_{i,t,t+j})(E_t \log Q_{t,t+j} - E_{t-1}\log Q_{t,t+j})\\
&\quad + \sum_{j=0}^{J_{i,t}}\pi_{i,t}\gamma_{i,t,t+j}(E_t \log Y_{i,t+j} - E_{t-1}\log Y_{i,t+j}).
\end{aligned} \tag{A.9}$$

By substituting equation (A.5) into equation (A.9) and replacing $Y_{i,t+j}$ with $Z'_{i,t+j}\varphi^y_t + P_{i,t+j} + \epsilon_{i,t+j}$, we can obtain

$$\begin{aligned}
\eta^c_{i,t} =& -\frac{1}{\sigma}\sum_{j=0}^{J_{i,t}}\theta_{i,t,t+j}(E_t Z'_{i,t+j}\varphi^p_{t+j} - E_{t-1}Z'_{i,t+j}\varphi^p_{t+j})\\
&+ \sum_{j=0}^{J_{i,t}}\pi_{i,t}\gamma_{i,t,t+j}(E_t Z'_{i,t+j}\varphi^y_{t+j} - E_{t-1}Z'_{i,t+j}\varphi^y_{t+j})\\
&+ \sum_{j=0}^{J_{i,t}}(\pi_{i,t}\gamma_{i,t,t+j} - (1-\frac{1}{\sigma})\theta_{i,t,t+j})(E_t \log Q_{t,t+j} - E_{t-1}\log Q_{t,t+j})\\
&+ \sum_{j=0}^{J_{i,t}}\pi_{i,t}\gamma_{i,t,t+j}(E_t(P_{i,t+j} + \epsilon_{i,t+j}) - E_{t-1}(P_{i,t+j} + \epsilon_{i,t+j}))\\
&+ \frac{1}{\sigma}\sum_{j=0}^{J_{i,t}-1}\left(\sum_{s=j+1}^{J_{i,t}}\theta_{i,t,t+s}\right)(E_t \log(1-\hat{\mu}_{i,t+j}) - E_{t-1}\log(1-\hat{\mu}_{i,t+j})).
\end{aligned} \tag{A.10}$$

By substituting equation (A.10) into equation (A.2), we can obtain

$$\begin{aligned}
\Delta \log C_{i,t} &= \frac{1}{\sigma}\Delta(Z'_{i,t}\varphi^p_t) + \frac{1}{\sigma}\log\beta + \frac{1}{\sigma}\log(1+r_{t-1}) - \frac{1}{\sigma}\log(1-\hat{\mu}_{i,t-1}) \\
&\quad - \frac{1}{\sigma}\sum_{j=0}^{J_{i,t}} \theta_{i,t,t+j}(E_t Z'_{i,t+j}\varphi^p_{t+j} - E_{t-1} Z'_{i,t+j}\varphi^p_{t+j}) \\
&\quad + \sum_{j=0}^{J_{i,t}} \pi_{i,t}\gamma_{i,t,t+j}(E_t Z'_{i,t+j}\varphi^y_{t+j} - E_{t-1} Z'_{i,t+j}\varphi^y_{t+j}) \\
&\quad + \sum_{j=0}^{J_{i,t}} (\pi_{i,t}\gamma_{i,t,t+j} - (1-\frac{1}{\sigma})\theta_{i,t,t+j})(E_t \log Q_{t,t+j} - E_{t-1}\log Q_{t,t+j}) \\
&\quad + \sum_{j=0}^{J_{i,t}} \pi_{i,t}\gamma_{i,t,t+j}(E_t(P_{i,t+j} + \epsilon_{i,t+j}) - E_{t-1}(P_{i,t+j} + \epsilon_{i,t+j})) \\
&\quad + \frac{1}{\sigma}\sum_{j=0}^{J_{i,t}-1}\left(\sum_{s=j+1}^{J_{i,t}} \theta_{i,t,t+s}\right)(E_t \log(1-\hat{\mu}_{i,t+j}) - E_{t-1}\log(1-\hat{\mu}_{i,t+j})).
\end{aligned} \tag{A.11}$$

I re-write equation (A.11) as follows.

- The first line of equation (A.11) includes $\Delta \log C_{i,t}$ on its left-hand-side. I decompose $\log C_{i,t}$ into the part explained by current observable characteristics and time, $Z'_{i,t}\varphi^c_t$, and the residual part, $c_{i,t}$. Then, $\Delta \log C_{i,t}$ can be re-written as $\Delta c_{i,t} + \Delta(Z'_{i,t}\varphi^c_t)$.

- In the first line of equation (A.11), $\frac{1}{\sigma}\log\beta + \frac{1}{\sigma}\log(1+r_{t-1})$ can be picked up by $Z_{i,t-1}$ and time. Therefore, I re-write this term as $Z'_{i,t-1}\varphi^{\beta,r}_{t-1}$.

- The first line of equation (A.11) includes $-\frac{1}{\sigma}\log(1-\hat{\mu}_{i,t-1})$. I decompose this term into the part explained by the history of aggregate shocks and observable characteristics up to period $t-1$, $\hat{E}_{t-1}[-\frac{1}{\sigma}\log(1-\hat{\mu}_{i,t-1})]$, and the residual part $\tilde{\mu}_{i,t-1}$, which can be written as

$$\tilde{\mu}_{i,t-1} := -\frac{1}{\sigma}\big\{\log(1-\hat{\mu}_{i,t-1}) - \hat{E}_{t-1}[\log(1-\hat{\mu}_{i,t-1})]\big\}.$$

- The second line of equation (A.11) is equal to

$$-\frac{1}{\sigma}\sum_{j=0}^{J_{i,t}}\theta_{i,t,t+j}(\hat{E}_t Z'_{i,t+j}\varphi^p_{t+j} - \hat{E}_{t-1}Z'_{i,t+j}\varphi^p_{t+j})$$

because $(\epsilon_t, \zeta_t)_t \perp (Z_{it}, \varphi_t^{p1}, \varphi_t^{y1}, \varphi_t^r)_t$. By the same reason, the third and the fourth lines of equation (A.11) can be re-written as

$$\sum_{j=0}^{J_{i,t}}\pi_{i,t}\gamma_{i,t,t+j}(\hat{E}_t Z'_{i,t+j}\varphi^y_{t+j} - \hat{E}_{t-1}Z'_{i,t+j}\varphi^y_{t+j})$$

and

$$\sum_{j=0}^{J_{i,t}}(\pi_{i,t}\gamma_{i,t,t+j} - (1-\frac{1}{\sigma})\theta_{i,t,t+j})(\hat{E}_t \log Q_{t,t+j} - \hat{E}_{t-1}\log Q_{t,t+j}),$$

respectively.

- In the fifth line of equation (A.11),

$$E_t(P_{i,t}+\epsilon_{i,t}) - E_{t-1}(P_{i,t}+\epsilon_{i,t}) = \zeta_{i,t}+\epsilon_{i,t}$$

and

$$E_t(P_{i,t+j}+\epsilon_{i,t+j}) - E_{t-1}(P_{i,t+j}+\epsilon_{i,t+j}) = \zeta_{i,t}, \quad j \geq 1.$$

Therefore, the fifth line of equation (A.11) can be re-written as $\pi_{i,t}\zeta_{i,t} + \pi_{i,t}\gamma_{i,t,t}\epsilon_{i,t}$.

- I denote the whole term in the sixth line of equation (A.11) as M_t, *i.e.*,

$$M_t := \frac{1}{\sigma}\sum_{j=0}^{J_{i,t}-1}\left(\sum_{s=j+1}^{J_{i,t}}\theta_{i,t,t+s}\right)(E_t\log(1-\hat{\mu}_{i,t+j}) - E_{t-1}\log(1-\hat{\mu}_{i,t+j})).$$

I decompose this term into the part explained by the history of aggregate shocks and observable characteristics up to period t, $\hat{E}_t M_t$, and the residual part $\tilde{M}_{i,t} := M_t - \hat{E}_t M_t$.

Then, equation (A.11) becomes

$$\Delta c_{i,t} = \tilde{\mu}_{i,t-1} + \pi_{i,t}\zeta_{i,t} + \pi_{i,t}\gamma_{i,t,t}\epsilon_{i,t} + \tilde{M}_{i,t} + \xi_{i,t} \tag{A.12}$$

in which

$$\begin{aligned}
\xi_{i,t} =& -\Delta(Z'_{i,t}\varphi^c_t) + \frac{1}{\sigma}\Delta(Z'_{i,t}\varphi^p_t) + Z'_{i,t-1}\varphi^{\beta,r}_{t-1} - \frac{1}{\sigma}\hat{E}_{t-1}[\log(1-\hat{\mu}_{i,t-1})] \\
& - \frac{1}{\sigma}\sum_{j=0}^{J_{i,t}} \theta_{i,t,t+j}(\hat{E}_t Z'_{i,t+j}\varphi^p_{t+j} - \hat{E}_{t-1} Z'_{i,t+j}\varphi^p_{t+j}) \\
& + \sum_{j=0}^{J_{i,t}} \pi_{i,t}\gamma_{i,t,t+j}(\hat{E}_t Z'_{i,t+j}\varphi^y_{t+j} - \hat{E}_{t-1} Z'_{i,t+j}\varphi^y_{t+j}) \\
& + \sum_{j=0}^{J_{i,t}} (\pi_{i,t}\gamma_{i,t,t+j} - (1-\frac{1}{\sigma})\theta_{i,t,t+j})(\hat{E}_t \log Q_{t,t+j} - \hat{E}_{t-1}\log Q_{t,t+j}) \\
& + \hat{E}_t M_t.
\end{aligned}$$

By construction, we have $Ec_{i,t} = Ec_{i,t-1} = E\tilde{\mu}_{i,t-1} = E\tilde{M}_{i,t} = 0$ (since they are defined as residuals). We also have $E[\pi_{i,t}\zeta_{i,t}] = E[\hat{E}_{t-1}[\pi_{i,t}\zeta_{i,t}]] = E[\pi_{i,t}\hat{E}_{t-1}[\zeta_{i,t}]] = E[\pi_{i,t}E[\zeta_{i,t}]] = 0$. In the same way, we can show $E[\pi_{i,t}\gamma_{i,t,t}\epsilon_{i,t}] = 0$. Therefore, from equation (A.12), we have

$$E\xi_{i,t} = 0.$$

Moreover, because $\xi_{i,t}$ is a function of $(Z_{i,t-s})_{s\geq 0}$, $(\varphi^{p1}_{t-s})_{s\geq 0}$, $(\varphi^{y1}_{t-s})_{s\geq 0}$, and $(r_{t-s})_{s\geq 0}$, we have

$$(\zeta_{i,t}, \epsilon_{i,t})_t \perp (\xi_{i,t})_t.$$

A.2 Details on Data

In this section, I provide details of the ENAHO survey, variable construction, and sample selection that are omitted in the main text for the sake of conciseness.

A.2.1 ENAHO Survey

ENAHO is a nationally representative household survey in Peru conducted by Instituto Nacional de Estadística e Informática (INEI), the national statistical office of Peru. This survey is conducted nationwide, covering both urban and rural areas. ENAHO targets people living in private dwellings but excludes inhabitants living in collective housing (such as people living in hospitals, barracks, police stations, hotels, asylums, religious cloisters, and detention centers, and armed forces living in barraks, camps, and boats).

In ENAHO, sample dwellings are selected from census data through multiple stages of stratified sampling. For the selected addresses, trained interviewers visit and collect data via face-to-face interview with the interviewees. ENAHO's manuals for pollsters (Instituto Nacional de Estadística e Informática, 2004, 2007, 2010-2016) indicate that interviewers make multiple visits whenever necessary to correct mistakes or recover missing information.

Table A.1 reports the non-response rates of each year documented in ENAHO's quality reports (Instituto Nacional de Estadística e Informática, 2009-2016) in which non-response rates are defined as 'the proportion of occupied dwellings of which informants do not want to be interviewed or are absent at the time of visit'. The average non-response rate during the sample years (2004-2016) is 7.5%. According to the quality reports, the non-response rates tend to be higher in urban areas than rural areas. Moreover, socioeconomic strata with higher income tend to exhibit higher non-response rates. These patterns raise a usual concern for surveys of this kind that rich households in urban areas are under-represented. In ENAHO, this concern is at least partially addressed by adjusting weights at a certain level of sampling strata reflecting geographic regions, urbanity, and socioeconomic status.

Table A.1: Non-response Rates in ENAHO

2004	2005	2006	2007	2008	2009	2010
9.0%	13.3%	7.9%	5.2%	6.8%	6.4%	7.2%
2011	2012	2013	2014	2015	2016	average
8.3%	6.8%	6.8%	6.6%	7.2%	6.6%	7.5%

Notes: The non-response rates of each year in this table are from ENAHO's quality reports (Instituto Nacional de Estadística e Informática, 2009-2016).

A.2.2 Variable Construction

My consumption measure for ENAHO builds on Kocherlakota and Pistaferri (2009)'s expenditure categories for Consumer Expenditure (CEX) Interview Survey. Most of their categories – such as food at home, food away from home, alcohol, apparel and footwear, clothing services, tobacco, heating, utilities, public transportation, gasoline and oil, vehicle maintenance and repairs, parking fees, newspapers and magazines, club membership fees, ticket admissions, miscellaneous entertainment expenses, home rent, home maintenance and repairs, telephone and cable, domestic services, other home services, personal care services, and miscellaneous rentals and repair – have corresponding expenditure items in ENANO.[3] In addition to them, I add two more expenditure categories including rental equivalence of owned or donated housing and daily nondurable goods.[4] Following Attanasio and Weber (1995) and Kocherlakota and Pistaferri (2009), I exclude health and education expenses from the consumption measure due to their durable nature.

The consumption measure of Kaplan et al. (2014b) is consistent with my consumption measure for ENAHO in that it is also composed of nondurable goods and a subset of services and that it also includes home rent and housing service from owned or donated housing. One notable difference

[3]Among Kocherlakota and Pistaferri (2009)'s expenditure categories, vehicle expenses, books, home insurance, and babysitting do not have corresponding expenditure items in ENAHO.

[4]Daily nondurable goods include laundry items such as detergent and bleach, bathroom items such as toilet papers and cleaning supplies, and daily care items such as soap, toothpaste, and shampoo. These items are not in CEX Interview Survey which Kocherlakota and Pistaferri (2009) use.

between the two consumption measures is that their consumption measure includes health and education expenses. Therefore, I adopt their consumption measure with one revision that health and education expenses are excluded.

Like many other household surveys, missing information is imputed in both expense and income items in ENAHO. Imputed components of income could be particularly problematic in identifying income shocks given that many households rely only on a small number of income sources. Therefore, I exclude the imputed income components from the income of Peruvian households. As discussed in subsection 1.3.2, I cannot do the same for the income of U.S. households, and therefore, I conduct a robustness check by consistently including the imputed components of Peruvian households' income in Appendix A.4.3.

Unlike the imputed components of income, I do not remove the imputed components of expense from the consumption of Peruvian households. Note that imputation is conducted only when households report that they obtain some items but do not report their values. Given that households obtain a variety of expense items, when households miss the values on a subset of expense items, reflecting the fact that households obtain these items using imputed values could still be helpful in measuring consumption responses.

In ENAHO, some expense items require judgment calls on determining their reference periods. ENAHO's questionnaires on expenditure proceed as follows. For each expense item, households are asked if they obtain it during period A. If the answer is yes, households are asked to report how much they spent on the item per period B. For most expense items, period A is equal to period B. Then, this period becomes the reference period for the expense item. However, there are cases in which period A and period B differ. For example, many food items have 'last 15 days' as period A, but households can choose period B. When period A and period B differ, I use the longer period between period A and period B as the reference period for the expense item.

As discussed in subsection 1.3.2, in ENAHO, individual households report more than 97 percent (in value) of expense items and income items, respectively, with reference periods shorter than or equal to the previous three months, on average. Specifically, individual households' ratio between 'items with reference periods longer than the previous three months' and 'items with all reference periods' for the baseline measure of consumption is 1.74 percent, on average. The ratio for the baseline measure of income is 2.51 percent, on average.

Both countries' income and consumption are deflated with CPI series. Regarding the deflation of Peruvian households' income and consumption, ENAHO provides within-year-deflated values of income and expense items (or, equivalently, values in terms of the CPI index of the survey year). For example, ENAHO provides the value of a household's food expense spent on February, 2004 in terms of the 2004 price level. In constructing the real income and consumption of Peruvian households, I aggregate these within-year-deflated values of income and expense items, respectively, and then, deflate the aggregated values using annual CPI series of Peru.

A.2.3 Sample Selection

Here, I provide details of the sample selection omitted in the main text. In the second step, gender and age are used as the criteria for determining whether the head of the household changes. In the sixth step, type-1 observations are dropped if any of their (i) baseline consumption measure, (ii) baseline income measure, and (iii) comprehensive income measure including imputed income components and income items with reference periods longer than the previous three months are zero or negative. In the seventh step, the criterion for 'having too much value' is set as follows. For each $(x, y) \in \{$(expense items with reference periods longer than the previous three months, baseline consumption measure), (income items with reference periods longer than the previous three months, baseline income measure), (income imputation, baseline income measure)$\}$, observations are dropped if $x/(x + y) > 0.05$. In the eighth step, I define income outliers as households whose income growth is in the range of the extreme 1 percent (0.5 percent at the top and 0.5 percent at the bottom) in the calendar-year subsamples at least one time. Table A.2 reports how many observations of each type are dropped in each step.

For the U.S. households, I adopt Kaplan et al. (2014b)'s sample selection with three minor revisions. First, they restrict household heads' ages to be between 25 and 55. I revise this age

Table A.2: Baseline Sample Selection for ENAHO

	type-1	type-2	type-3
initial sample	113,329	74,667	36,005
months not matched, fake type-2 obs., or head changed	100,282	64,103	27,924
incomplete survey	86,396	49,738	20,295
age restriction, 25-65	67,681	38,380	15,496
observable characteristics missing	67,384	38,314	15,493
non-positive Y and C	66,961	37,863	15, 244
too much imputation in Y or 3ml in Y, C	47,819	22,354	7,666
outliers on income growth	47, 210	21, 988	7,509

Notes: In the penultimate line of the table, '3ml' is an abbreviation for 'items with reference periods longer than the previous three months'.

restriction to be between 25 and 65 for the sake of consistent sample selection with the Peruvian sample. In Appendix A.4.10 and B.2.6, I conduct a robustness check by revising the age restriction of both the U.S. and Peruvian samples to be between 25 and 55. Second, when controlling consumption and income with observable characteristics, Kaplan et al. (2014b) use only type-1 observations that belong to at least one type-3 observation. I additionally use type-1 observations that belong to at least one type-2 observation when controlling consumption and income with observable characteristics and constructing income distribution. Third, there are type-1 observations that miss either income or consumption, but not both. Kaplan et al. (2014b) allow them to be used when controlling income and consumption with observable characteristics. For example, if a type-1 observation misses income but does not miss consumption, it is used in controlling consumption. Instead, I use only type-1 observations that do not miss both income and consumption when controlling income and consumption with observable characteristics.

A remaining difference between Kaplan et al. (2014b)'s sample selection and my ENAHO sample selection is the criteria for income outliers. Kaplan et al. (2014b) categorize households as income outliers if their nominal income is below 100 Dollars or their income growth is greater than 5 or less than -0.8 at least one time. I do not use this criteria in my baseline selection for the Peruvian sample because it is not straightforward to determine the right cutoffs for Peruvian households reflecting cross-country differences including the difference in growth units (the two-year-over-two-year growth of annual income for U.S. households, the year-over-year growth of quarterly income for Peruvian households). In Appendix A.4.11 and B.2.7, I conduct a robustness check by defining Peruvian income outliers in a more similar fashion with Kaplan et al. (2014b), despite the difficulty of finding the right corresponding cutoffs.

A.2.4 Detecting Potentially Fake Type-2 Observations

In ENAHO, panel observations are selected based on addresses. When an old household moves away and a new household moves into an address selected for a panel interview, ENAHO's manuals for pollsters (Instituto Nacional de Estadística e Informática, 2004, 2007, 2010-2016) indicate that the interview proceeds with the new household. However, the manual does not specify whether the observation on the new household will be distinguished from the previous observations on the old household or it will be falsely linked to the observations and create a fake type-2 observation. The latter case is problematic for the analyses of this paper.

Fortunately, there is an effective way to identify type-2 observations that are subject to this problem. ENAHO tracks not only households but also their members over time. Specifically, variable 'p215' records each household member's year-specific identification number (the unique number assigned in each year's survey to enumerate each member from 1 onward) in the previous year. This variable makes it possible to track household members over time. When two different households are falsely linked as a type-2 observation, we will observe that either household members are not linked by variable 'p215' or different persons are falsely linked by variable 'p215'. At persons' level, it is easier to determine whether the two persons linked by variable 'p215' are the same person since ENAHO collects household members' date of birth (dd/mm/yyyy) and gender. If two persons linked by variable 'p215' have the same birth date and gender, it is highly likely that they are the same person. And if the same person appears in the two households linked as a type-2 observation, it is highly likely that this type-2 observation is correctly tracking the same household over time. On the other hand, if we cannot verify any common person appearing in two households linked as a type-2 observation, it is not free from the problem of linking two different households.

Based on this logic, I link household members over time using variable ‘p215’, and identify linked persons whose date of birth and gender are exactly equal in the two interviews. I name them ‘verified same members’. Despite a nontrivial chance that household members’ birth dates are not exactly reported, it turns out that most type-2 observations do have at least one verified same member. I identify type-2 observations that do not have any verified same member, and define them as ‘potentially fake type-2 observations’. I drop them in the sample selection.

Combined with the other steps of the sample selection, a selected type-2 observation satisfies the following conditions: it connects households that (i) live in the same address, (ii) have at least one verified same member, and (iii) have heads with the same age and gender. It is highly likely that such a type-2 observation correctly tracks the same household over time. In Appendix A.4.13 and B.2.9, I apply even a stricter rule in detecting potentially fake type-2 observations at the cost of a smaller sample size as follows: if the number of verified same members of a type-2 observation is less than half of the household size for any of the two households connected as the type-2 observation, I identify it as a potentially fake type-2 observation and drop it.[5] The main findings are robust to applying this stricter rule.

A.3 MPC Estimates and Standard Errors in Numerical Values

In this section, I report the numerical values of the MPC estimates and standard errors plotted in Figure 1.1.

[5]Under the stricter rule, the number of type-3 observations shrinks from 7,509 to 6,324.

Table A.3: Annual MPCs of the Income Deciles in Peru and the U.S.

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Peru	0.942	0.668	0.666	0.671	0.678	0.654	0.660	0.528	0.556	0.299
	(0.052)	(0.104)	(0.091)	(0.087)	(0.083)	(0.080)	(0.075)	(0.084)	(0.082)	(0.086)
N	758	827	833	787	730	699	724	743	704	704
U.S.	0.160	0.096	0.083	0.129	0.123	0.077	0.087	0.077	0.023	0.036
	(0.083)	(0.050)	(0.043)	(0.045)	(0.030)	(0.029)	(0.032)	(0.030)	(0.034)	(0.017)
N	1,332	1,467	1,504	1,539	1,573	1,560	1,567	1,472	1,413	1,363

Notes: The estimates and the standard errors reported in this table are used to plot Figure 1.1.

A.4 Robustness for the MPC Estimation

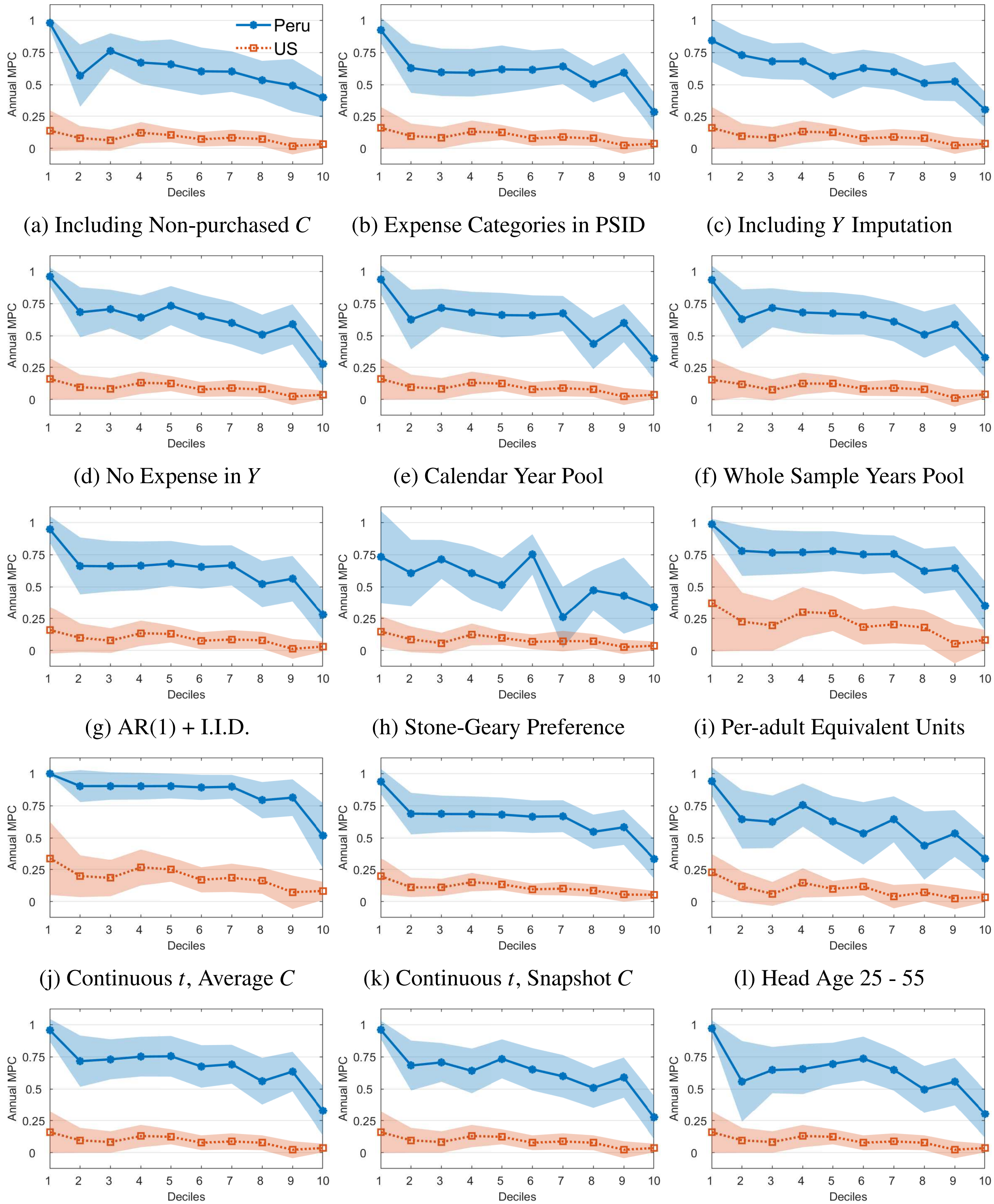
In this subsection, I present the results of the robustness checks that I conduct regarding the MPC estimation. Each panel of Figure A.1 plots the result of each robustness check. These panels in Figure A.1 verify that the main findings in Figure 1.1 – (i) the mean MPC being substantially higher and (ii) within-country MPC heterogeneity over the income distribution being substantially stronger in Peru than in the U.S.– are robust to the following alternative setups.

A.4.1 Including Non-purchased Consumption

In the baseline consumption measure, I exclude non-purchased consumption such as donations, food stamps, in-kind income, and self-production. In this robustness check, I use an alternative consumption measure that includes the non-purchased consumption. Figure A.1a plots the result.

A.4.2 Restricting Expense Categories to Those Available in the PSID

Due to the lack of coverage in the early waves in the U.S. sample, the baseline consumption of U.S. households does not include clothing, recreation, alcohol, and tobacco, while the baseline consumption of Peruvian households includes them. Here, I conduct a robustness check by consistently excluding these expenses from the consumption of Peruvian households. Figure A.1b plots the result.



(a) Including Non-purchased C (b) Expense Categories in PSID (c) Including Y Imputation

(d) No Expense in Y (e) Calendar Year Pool (f) Whole Sample Years Pool

(g) AR(1) + I.I.D. (h) Stone-Geary Preference (i) Per-adult Equivalent Units

(j) Continuous t, Average C (k) Continuous t, Snapshot C (l) Head Age 25 - 55

(m) Alternative Income Outliers (n) Male Heads Only (o) Stricter Rule for Fake Type-2

Figure A.1: Robustness – Annual MPCs

Notes: In the x-axis of each panel, 1 is the bottom decile. Shaded areas represent 95% confidence intervals.

A.4.3 Including Imputed Income Components

The baseline income measure for the Peruvian sample excludes imputed income components. Moreover, I drop observations that include too much value in the imputed income components in the Peruvian sample selection. These treatments are not available in the U.S. sample because the imputed components of income are not distinguishable in Kaplan et al. (2014b)'s dataset. Here, I conduct a robustness check by consistently including the imputed components of Peruvian households' income. Moreover, the observations with too much value in the imputed income components are not dropped. Figure A.1c plots the result.

A.4.4 Excluding Expense Items from Income

The income measure for ENAHO includes two expense items that are also included in the consumption of Peruvian households: rental equivalence of housing provided by work and rental equivalence of donated housing. On the other hand, the income of U.S. households does not include any expense items that are included in their consumption. Here, I conduct a robustness check by consistently excluding the two expense items from Peruvian households' income. Figure A.1d plots the result.

A.4.5 Sorting Income ($y_{i,t}$) in Different Observation Pools

In the baseline analysis, I sort unpredictable component of income $y_{i,t}$ within each calendar year for the U.S. sample and within each calendar quarter for the Peruvian sample, in accordance with the unit time length of each sample (a year for the U.S. sample, a quarter for the Peruvian sample). However, because I already remove the time-fixed effect when controlling for the predictable components (annually for the U.S. sample, quarterly for the Peruvian sample), it should also be fine to sort unpredictable component of income $y_{i,t}$ in a larger observation pool than the pool of the unit time length. In this robustness check, I sort income in different observation pools such as (i) the pool of each calender year (not only for the U.S. sample, but also for the Peruvian sample), and (ii) the pool of the whole sample years. Figure A.1e and Figure A.1f plot the MPC estimation results under the pool of each calendar year and the pool of the whole sample years, respectively.

A.4.6 Replacing the Permanent Component of Income with an AR(1) Process

In the baseline analysis, the unpredictable component of income $y_{i,t}$ is assumed to be composed of a permanent component and a transitory component, following Blundell et al. (2008) and Kaplan et al. (2014b). This income process is restrictive in that an income shock cannot have a persistent effect without being permanent. Kaplan and Violante (2010) propose a way to identify Blundell et al. (2008)'s partial insurance parameters under an alternative income process composed of an AR(1) component and a transitory component. Adopting their identification strategy, I estimate the MPCs under the alternative income process.

The identification strategy works as follows. Assume that households' income $Y_{i,t}$ is determined by

$$\log Y_{i,t} = Z'_{i,t}\varphi^y_t + P_{i,t} + \epsilon_{i,t},$$

$$P_{i,t} = \rho P_{i,t-1} + \zeta_{i,t},$$

$$\zeta_{i,t} \sim_{iid} (0, \sigma^2_{ps}), \quad \epsilon_{i,t} \sim_{iid} (0, \sigma^2_{tr}), \quad (\zeta_{i,t})_t \perp (\epsilon_{i,t})_t, \quad \text{and}$$

$$(Z_{i,t})_t \perp (\zeta_{i,t}, \epsilon_{i,t})_t.$$

As before, $y_{i,t} := \log Y_{i,t} - Z'_{i,t}\varphi^y_t$ represents the unpredictable component of income. Let

$$\tilde{\Delta}^K y_{i,t} := y_{i,t} - \rho^K y_{i,t-K}.$$

Then we have

$$\tilde{\Delta}^K y_{i,t} = \sum_{s=0}^{K-1} \rho^s \zeta_{i,t-s} + \epsilon_{i,t} - \rho^K \epsilon_{i,t-K} \tag{A.13}$$

for any $K \geq 1$. As in equation (1.11), the partial insurance parameter to transitory income shocks

ψ_G for each group G is defined as follows.

$$\psi_G := \frac{cov[\Delta c_{i,t}, \epsilon_{i,t}|(i,t) \in G]}{cov[\Delta y_{i,t}, \epsilon_{i,t}|(i,t) \in G]}.$$

When the grouping of observation (i,t)'s is independent of $\epsilon_{i,t}$, the characterization of ψ_G in equation (1.12) still holds under the alternative income process as follows.

$$\psi_G = \psi_G^{PIH} + \frac{cov[\epsilon_{i,t}, \tilde{M}_{i,t}|(i,t) \in G]}{var[\epsilon_{i,t}|(i,t) \in G]}.$$

When the grouping of observation (i,t)'s is independent of $(\zeta_{i,t+j}, \epsilon_{t+j})_{j \geq 0}$, we can derive

$$\psi_G = \frac{cov[\Delta^K c_{it}, \tilde{\Delta}^K y_{i,t+K}|(i,t) \in G]}{cov[\tilde{\Delta}^K y_{it}, \tilde{\Delta}^K y_{i,t+K}|(i,t) \in G]} \tag{A.14}$$

from equations (1.10) and (A.13).

To identify ψ_G using equation (A.14), we need to know the value of ρ^K to compute $\tilde{\Delta}^K y_{i,t}$ and $\tilde{\Delta}^K y_{i,t+K}$. I estimate ρ^K using the following equation.

$$\rho^K = \frac{cov[y_{i,t}, y_{i,t-2K}]}{cov[y_{i,t-K}, y_{i,t-2K}]} = \frac{\rho^{2K} var(P_{i,t-2K})}{\rho^K var(P_{i,t-2K})}. \tag{A.15}$$

In the Peruvian sample, the estimate (standard error[6]) of ρ^4 is 0.939 (0.020). Since the time unit is a quarter, the estimate of ρ^4 represents Peruvian households' annual autocorrelation coefficient for their persistent income shocks. In the U.S. sample, the estimate (standard error) of ρ^2 is 0.923 (0.010). Since the time unit is a year, the estimate of ρ^2 represents U.S. households' biannual autocorrelation coefficient for their persistent income shocks. The fact that the estimates of ρ^K for both countries are close to 1 assures that the specification of the income process imposed in the baseline analysis (random walk + i.i.d) is not seriously flawed.

Figure A.1g plots the MPCs I estimate using equation (A.14), the estimates of ρ^K from equation (A.15), and equation (1.14).

[6]In the estimation, standard errors are clustered within each household.

A.4.7 Incorporating a Subsistence Point into the Preference

Consumption being close to a subsistence level is more likely in Peru than in the U.S. In this robustness check, I estimate MPCs after incorporating a subsistence level into the model. Specifically, I replace the household uitility function of the baseline model with the one developed by Stone (1954) and Geary (1950) under which households obtain utility only from consumption beyond a subsistence point. Under the Stone-Geary preference, households solve the following problem.

$$\max_{\{C_{i,t+j},A_{i,t+j}\}_{j=0}^{J_{i,t}}} E\left[\sum_{j=0}^{J_{i,t}} \beta^j e^{(Z'_{i,t+j}\varphi^p_{t+j})} \frac{(C_{i,t+j} - \underline{C})^{1-\sigma}}{1-\sigma} \middle| \mathbf{S}_{i,t}\right]$$

$$s.t.$$

$$C_{i,t+j} + A_{i,t+j} = Y_{i,t+j} + (1 + r_{t+j-1})A_{i,t+j-1}, \quad 0 \le j \le J_{i,t}, \tag{SBC}$$

$$A_{i,t+j} \ge 0, \quad 0 \le j \le J_{i,t} - 1, \tag{LQC}$$

$$A_{i,t+J_{i,t}} \ge 0 \tag{NPG}$$

in which $\underline{C}$ represents the subsistence point of consumption. To make sure the problem is well-defined, I assume that households' income $Y_{i,t}$ is always greater than $\underline{C}$ and is determined by

$$\log(Y_{i,t} - \underline{C}) = Z'_{i,t}\varphi^{y*}_t + P_{i,t} + \epsilon_{i,t},$$

$$P_{i,t} = P_{i,t-1} + \zeta_{i,t},$$

$$\zeta_{i,t} \sim_{iid} (0, \sigma^2_{pm}), \quad \epsilon_{i,t} \sim_{iid} (0, \sigma^2_{tr}), \quad (\zeta_{i,t})_t \perp (\epsilon_{i,t})_t, \quad \text{and}$$

$$(Z_{i,t})_t \perp (\zeta_{i,t}, \epsilon_{i,t})_t.$$

Let

$$C_{i,t}^* := C_{i,t} - \underline{C}, \quad \text{and}$$
$$Y_{i,t}^* := Y_{i,t} - \underline{C}. \tag{A.16}$$

By substituting equation (A.16) into the households' problem and the income process specified above, we can observe that the model with Stone-Geary preference is isomorphic to the baseline model in subsection 1.2.1, except for $(C_{i,t}, Y_{i,t})$ of the baseline model being replaced with $(C_{i,t}^*, Y_{i,t}^*)$. Exploiting this isomorphism, we can estimate the annual MPC using the following equations.

$$\psi_G = \frac{cov[\Delta^K c_{it}^*, \Delta^K y_{i,t+K}^* | (i,t) \in G]}{cov[\Delta^K y_{it}^*, \Delta^K y_{i,t+K}^* | (i,t) \in G]}, \quad K \geq 1, \quad \text{and} \tag{A.17}$$

$$MPC_G = \psi_G \frac{E[C_{i,t-K}^* | (i,t) \in G]}{E[Y_{i,t-K}^* | (i,t) \in G]}. \tag{A.18}$$

in which $c_{i,t}^* := \log C_{i,t}^* - Z_{i,t}' \varphi_t^{c*}$ is the unpredictable component of $\log C_{i,t}^*$ and $y_{i,t}^* := \log Y_{i,t}^* - Z_{i,t}' \varphi_t^{y*}$ is the unpredictable component of $\log Y_{i,t}^*$.

When computing $C_{i,t}^*$ and $Y_{i,t}^*$ using equation (A.16), I use the consumption measure including non-purchased consumption for $C_{i,t}$ and the baseline measure of income for $Y_{i,t}$. I calibrate the subsistence point $\underline{C}$ to be equal to one of the poverty lines that World Bank uses, \$ 3.20 per day in 2011 International Dollar. Observations with $C_{i,t} \leq \underline{C}$ or $Y_{i,t} \leq \underline{C}$ are dropped. The unpredictable components, $c_{i,t}^*$ and $y_{i,t}^*$ are constructed by controlling for the predictable components from $\log C_{i,t}^*$ and $\log Y_{i,t}^*$. As in the baseline analysis, when constructing income groups I include observations dropped due to having too much value in imputed income components or to having too much value in items with reference periods longer than the previous three months. For the purpose of income sorting, I use the unpredictable component of the comprehensive income measure (which includes not only the baseline measure of income but also the income items with reference periods longer than the previous three months and the imputed income components) minus the subsistence point, $\underline{C}$. Figure A.1h plots the result of the MPC estimation.

A.4.8 Treating Unpredictable Components as Per-Adult Equivalent Units

In the model discussed in subsection 1.2.1, the vector of observable characteristics $Z_{i,t}$ appears in two places: one in the preference shift $Z'_{i,t}\varphi^p_t$ and the other in the predictable component of income $Z'_{i,t}\varphi^y_t$. They appear in these places to make the model consistent with the data pattern that a sizable portion of income and consumption variations are explained by observable characteristics.

Some studies such as Guvenen and Smith (2014) do not have these terms in the model and instead assume that the residuals of income and consumption after controlling for observable characteristics are income and consumption of per-adult equivalent units, and the residuals should be explained by the model. This alternative approach does not affect the estimation of Blundell et al. (2008)'s partial insurance parameters, but affects which consumption-to-income ratio to be multiplied in converting the partial insurance parameters to MPC. In the baseline analysis, I use $\frac{E[C_{i,t-K}|(i,t)\in G]}{E[Y_{i,t-K}|(i,t)\in G]}$, as described in equation (1.14). Note that both $C_{i,t-K}$ and $Y_{i,t-K}$ include the predictable components $Z'_{i,t-K}\varphi^c_{t-K}$ and $Z'_{i,t-K}\varphi^y_{t-K}$. On the other hand, in the approach of treating $c_{i,t}$ and $y_{i,t}$ as the log consumption and log income of per-adult equivalent units, $\frac{E[\exp(c_{i,t-K})|(i,t)\in G]}{E[\exp(y_{i,t-K})|(i,t)\in G]}$ should be multiplied, instead.

In this robustness check, I take this alternative approach and estimate MPCs by multiplying the Blundell et al. (2008)'s partial insurance parameters with $\frac{E[\exp(c_{i,t-K})|(i,t)\in G]}{E[\exp(y_{i,t-K})|(i,t)\in G]}$. Figure A.1i plots the MPC estimation result under this approach.

A.4.9 Addressing the Time Aggregation Problem and the Time Inconsistency Problem in a Continuous Time Model

As Crawley (2019) notes, continuous-time models are useful in dealing with two possible issues in discrete time models: the time aggregation problem and the time inconsistency problem. The time aggregation problem means that a completely transitory shock in a continuous-time process can generate an autocorrelation in a discrete-time process constructed by aggregating the continuous-time process over a specified period. The time inconsistency problem means the reference period for consumption could be inconsistent with the reference period for income because of the intended design of a survey, unclear description of questionnaires, and greater difficulties in recalling memory regarding expenses. In this robustness check, I address these issues using a continuous-time model, as in Crawley (2019).

Crawley (2019) presents a continuous-time model in which a level income process and a level consumption function are specified (instead of a log income process and a log consumption function) because level variables are more convenient to aggregate over time than log variables. In the model, the level consumption follows a random walk that moves only in response to current shocks on the level income. Then, the author shows in appendix that the identifying equations in the continuous-time model with the level specifications become equal to the identifying equations in a discrete-time model with log specifitaions under a first-order approximation as the discrete timeframe approaches to a continuous one in a limit. However, the income process specified in the author's discrete-time model is different from the income process in Blundell et al. (2008). Moreover, it is not clear how the consumption function should be specified in the discrete-time model for the equivalence of the identifying equations between the discrete-time model and the continuous-time model.[7]

The model presented here is borrowed from Crawley (2019) but with two modificiations. First, as in the appendix of Crawley (2019), I begin from a discrete-time model with log specifications, derive the identifying equations under a first-order approximation, and obtain their limits as the discrete timeframe approaches to a continuous one, but I use a different first-order approximation which allows my discrete-time model to have the same income process as the one in Blundell et al. (2008). Second, I specify the consumption function in such a way that the dynamic consumption responses to a transitory income shock decay exponentially over time.[8]

As in the appendix of Crawley (2019), I begin with a discrete-time model with m sub-periods.

[7]Crawley (2019)'s appendix only shows the equivalence of the identifying equation for the variance in income growth.

[8]This specification is consistent with Auclert (2019)'s conversion formula between quarterly MPC and annual MPC. Admittedly, however, the consumption function is not derived from the optimality condition of households' problem. Deriving testable implications from the optimality conditions of a continuous-time model (or from the optimality conditions of a discrete-time model in a continuous-time limit), would be an interesting extension in this line of investigation.

I enumerate the discrete time index for the sub-periods t as $t = \frac{1}{m}, \frac{2}{m}, \cdots, \frac{m-1}{m}, 1, 1 + \frac{1}{m}, \cdots$. The time length of 1 in the t-axis (*i.e.*, $\Delta t = 1$) corresponds to the unit time length of the observations. It is a quarter in the Peruvian sample and a year in the U.S. sample. $Y_{i,t}$ and $C_{i,t}$ represent income and consumption during sub-period t. $\bar{Y}_T$ and $\bar{C}_T$ represent the total income and consumption during the period of the unit time length ($\Delta t = 1$) ending at $t = T$. In other words,

$$\bar{Y}_T := Y_{i,T-1+\frac{1}{m}} + Y_{i,T-1+\frac{2}{m}} + \cdots + Y_{i,T} \tag{A.19}$$

and

$$\bar{C}_T := C_{i,T-1+\frac{1}{m}} + C_{i,T-1+\frac{2}{m}} + \cdots + C_{i,T}. \tag{A.20}$$

The log income process and the log consumption function are specified as follows.

$$\log Y_{i,t} = P_{i,t} + \epsilon_{i,t} \tag{A.21}$$

in which

$$P_{i,t} = P_{i,t-\frac{1}{m}} + \zeta_{i,t},$$

$$\zeta_{i,t} \sim_{iid} (0, \sigma^2_{pm,m}), \quad \epsilon_{i,t} \sim_{iid} (0, \sigma^2_{tr,m}), \quad (\zeta_{i,t})_t \perp (\epsilon_{i,t})_t.$$

$$\Delta^{\frac{1}{m}} \log C_{i,t} = \phi\zeta_{i,t} + \sum_{k=0}^{\infty} \psi_{\frac{k}{m}} \epsilon_{i,t-\frac{k}{m}} \tag{A.22}$$

in which $\Delta^s x_t := x_t - x_{t-s}$ for any time-series $(x_t)_t$ and any $s > 0$. As in the main text, I omit s from Δ^s when $s = 1$.

Let

$$\Psi_{\frac{j}{m}} := \psi_0 + \psi_{\frac{1}{m}} + \cdots + \psi_{\frac{j}{m}}$$

and

$$\overrightarrow{\Psi}_{\frac{j}{m}} := \Psi_{\frac{0}{m}} + \Psi_{\frac{1}{m}} + \cdots + \Psi_{\frac{j}{m}}.$$

By summing up equation (A.22) over j sub-periods, we get

$$\Delta^{\frac{j}{m}} \log C_{i,t+j} = \big(\psi_0 + \psi_{\frac{1}{m}} + \cdots + \psi_{\frac{j}{m}}\big)\epsilon_{i,t} + \big(\text{other terms unrelated with } \epsilon_{i,t}\big).$$

Therefore, the dynamic consumption response in sub-period $t + j$ to a transitory income shock in sub-period t is $\left(\Psi_{\frac{j}{m}} \cdot \frac{E[C]}{E[Y]}\right)$. The MPC out of a transitory income shock during the period of the unit length ($\Delta t = 1$) after the shock (or, equivalently, the cumulative consumption response to the shock during the period) is

$$MPC = \overrightarrow{\Psi}_{\frac{m-1}{m}} \cdot \frac{E[C]}{E[Y]}. \tag{A.23}$$

From equation (A.19), we have

$$\log(\bar{Y}_{i,T}) = \log\big(\sum_{j=1}^{m} \exp(\log Y_{i,T-1+\frac{j}{m}})\big).$$

By first-order-Taylor-approximating $\log Y_{i,T-1+\frac{j}{m}}$ around $E_{T-1} \log(\frac{1}{m}\bar{Y}_{i,T})$ for $j = 1, \cdots, m$ in this equation, we can obtain

$$\log(\bar{Y}_{i,T}) \approx \frac{1}{m} \sum_{j=1}^{m} \log Y_{i,T-1+\frac{j}{m}} + \log m. \tag{A.24}$$

In the same way, equation (A.20) can be re-written as

$$\log(\bar{C}_{i,T}) = \log\big(\sum_{j=1}^{m} \exp(\log C_{i,T-1+\frac{j}{m}})\big).$$

By first-order-Taylor-approximating $\log C_{i,T-1+\frac{j}{m}}$ around $E_{T-1} \log(\frac{1}{m}\bar{C}_{i,T})$ for $j = 1, \cdots, m$ in this equation, we can get

$$\log(\bar{C}_{i,T}) \approx \frac{1}{m} \sum_{j=1}^{m} \log C_{i,T-1+\frac{j}{m}} + \log m. \tag{A.25}$$

Let $Y_{i,T}^{obs}$ and $C_{i,T}^{obs}$ be the observed income and consumption in the data during period T. In terms of the relationship between the variables in the model and the variables observed in the data, I consider three cases: (i) $(Y_{i,T}^{obs}, C_{i,T}^{obs}) = (\bar{Y}_{i,T}, \bar{C}_{i,T})$, (ii) $(Y_{i,T}^{obs}, C_{i,T}^{obs}) = (\bar{Y}_{i,T}, C_{i,T})$, and (iii)

$(Y_{i,T}^{obs}, C_{i,T}^{obs}) = (Y_{i,T}, \bar{C}_{i,T})$.

Regarding the time inconsistency problem, the first case does not have it as the reference period of the observed income matches that of the observed consumption. In the second case, the observed consumption is the consumption flow during the last sub-period of the reference period for the observed income. This case has the time inconsistency problem in such a way that the reference period for the observed income is longer than that of the observed consumption. In the third case, the observed income is the income flow during the last sub-period of the reference period for the observed consumption. In this case, the time inconsistency problem is present in such a way that the reference period for the observed income is shorter than that for the observed consumption. As discussed in footnote 19 of subsection 1.3.2, the PSID is subject to the time inconsistency problem of the second case, while ENAHO is subject to the time inconsistency problems of both the second and third cases.

The time aggregation problem is present when the observed income is an aggregated income over multiple sub-periods. Therefore, the first and the second cases have the time aggregation problem, while the third case does not.

Case 1. When $(Y_{i,T}^{obs}, C_{i,T}^{obs}) = (\bar{Y}_{i,T}, \bar{C}_{i,T})$

Let

$$y_{i,T}^{obs} := \log Y_{i,T}^{obs}, \quad \text{and}$$
$$c_{i,T}^{obs} := \log C_{i,T}^{obs}.$$

From equation (A.24) and (A.25), we have

$$\Delta y_{i,T}^{obs} = \Delta \log Y_{i,T}^{obs} = \frac{1}{m} \sum_{j=1}^{m} \left(\log Y_{i,T-1+\frac{j}{m}} - \log Y_{i,T-2+\frac{j}{m}} \right) \tag{A.26}$$

and

$$\Delta c_{i,T}^{obs} = \Delta \log C_{i,T}^{obs} = \frac{1}{m} \sum_{j=1}^{m} \left(\log C_{i,T-1+\frac{j}{m}} - \log C_{i,T-2+\frac{j}{m}} \right) \tag{A.27}$$

By substituting equations (A.21) and (A.22) into (A.26) and (A.27) and computing variances and covariances of the observed income growth $\Delta y_{i,T}^{obs}$ and consumption growth $\Delta c_{i,T}^{obs}$, we can obtain the following equations.

$$var[\Delta y_{i,T}^{obs}] = \left(\frac{1}{m} + \frac{(m-1)(2m-1)}{3m^2}\right)(m\sigma_{pm,m}^2) + 2\left(\frac{\sigma_{tr,m}^2}{m}\right),$$

$$cov[\Delta y_{i,T}^{obs}, \Delta y_{i,T+1}^{obs}] = \frac{m^2-1}{6m^2}(m\sigma_{pm,m}^2) - \left(\frac{\sigma_{tr,m}^2}{m}\right),$$

$$cov[\Delta y_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2,$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T}^{obs}] = \phi\frac{2m^2+1}{3m^2}(m\sigma_{pm,m}^2) + \frac{1}{m}\left\{\sum_{j=0}^{m-1}(3\overrightarrow{\Psi}_{\frac{j}{m}} - \overrightarrow{\Psi}_{1+\frac{j}{m}})\right\}\left(\frac{\sigma_{tr,m}^2}{m}\right),$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+1}^{obs}] = \phi\frac{m^2-1}{6m^2}(m\sigma_{pm,m}^2) - \frac{1}{m}(\sum_{j=0}^{m-1}\overrightarrow{\Psi}_{\frac{j}{m}})\left(\frac{\sigma_{tr,m}^2}{m}\right),$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2,$$

$$\begin{aligned} cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T-1}^{obs}] = \frac{m^2-1}{6m^2}\phi(m\sigma_{pm.m}^2) + \frac{1}{m}\Bigg\{ &\sum_{j=0}^{m-1}(\overrightarrow{\Psi}_{1+\frac{j}{m}} - 2\overrightarrow{\Psi}_{\frac{j}{m}}) \\ &- \sum_{j=0}^{m-1}(\overrightarrow{\Psi}_{2+\frac{j}{m}} - 2\overrightarrow{\Psi}_{1+\frac{j}{m}} + \overrightarrow{\Psi}_{\frac{j}{m}})\Bigg\}\left(\frac{\sigma_{tr,m}^2}{m}\right), \end{aligned}$$

$$\begin{aligned} cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T-N}^{obs}] = \frac{1}{m}\Bigg\{ &\sum_{j=0}^{m-1}(\overrightarrow{\Psi}_{N+\frac{j}{m}} - 2\overrightarrow{\Psi}_{N-1+\frac{j}{m}} + \overrightarrow{\Psi}_{N-2+\frac{j}{m}}) \\ &- \sum_{j=0}^{m-1}(\overrightarrow{\Psi}_{N+1+\frac{j}{m}} - 2\overrightarrow{\Psi}_{N+\frac{j}{m}} + \overrightarrow{\Psi}_{N-1+\frac{j}{m}})\Bigg\}\left(\frac{\sigma_{tr,m}^2}{m}\right), \quad N \geq 2. \end{aligned}$$

Now let's consider a limit in which m approaches infinity, *i.e.*, the discrete-time model approaches a continuous-time model. For the model in the limit to be stationary, we should have

$$\sigma_{pm}^2 := \lim_{m\to\infty} m\sigma_{pm,m}^2 < \infty \tag{A.28}$$

and

$$\sigma_{tr}^2 := \lim_{m\to\infty} \frac{\sigma_{tr,m}^2}{m} < \infty \tag{A.29}$$

Moreover, I assume that the dynamic consumption response to a past transitory shock $\Psi_{\frac{j}{m}}$ decays exponentially over time. In the continuous-time model, this assumption becomes

$$\Psi_t = \tau\lambda e^{-\lambda t}, \quad t \in [0, \infty) \tag{A.30}$$

for $\lambda > 0$ and $\tau > 0$, and

$$\overrightarrow{\Psi}_t = \int_0^t \Psi_t dt = \tau(1 - e^{-\lambda t}), \quad t \in [0, \infty). \tag{A.31}$$

Under equations (A.28), (A.29), (A.30), and (A.31), we have the following equations for variances and covariances of the continuous-time model in the limit.

$$var[\Delta y_{i,T}^{obs}] = \frac{2}{3}\sigma_{pm}^2 + 2\sigma_{tr}^2, \tag{A.32}$$

$$cov[\Delta y_{i,T}^{obs}, \Delta y_{i,T+1}^{obs}] = \frac{1}{6}\sigma_{pm}^2 - \sigma_{tr}^2, \tag{A.33}$$

$$cov[\Delta y_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2, \tag{A.34}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T}^{obs}] = \frac{2}{3}\phi\sigma_{pm}^2 + \tau\{2 - \frac{1}{\lambda}(1 - e^{-\lambda})(3 - e^{-\lambda})\}\sigma_{tr}^2, \tag{A.35}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+1}^{obs}] = \frac{\phi}{6}\sigma_{pm}^2 - \tau\{1 - \frac{1}{\lambda}(1 - e^{-\lambda})\}\sigma_{tr}^2, \tag{A.36}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2, \tag{A.37}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T-1}^{obs}] = \frac{\phi}{6}\sigma_{pm}^2 + \tau\{-1 + \frac{1}{\lambda}(1 - e^{-\lambda})(e^{-2\lambda} - 3e^{-\lambda} + 3)\}\sigma_{tr}^2, \tag{A.38}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T-N}^{obs}] = -\tau\frac{1}{\lambda}e^{-\lambda(N-2)}(1 - e^{-\lambda})^4\sigma_{tr}^2, \quad N \geq 2. \tag{A.39}$$

From equations (A.32), (A.33), (A.34), (A.35), (A.36), (A.37), (A.38), and (A.39), we can obtain the variances and covariances of $\Delta^K c_{i,T}^{obs}$ and $\Delta^K y_{i,T}^{obs}$ for $K = 2$ and $K = 4$ as follows.

$$var[\Delta^2 y_{i,T+2}^{obs}] = \frac{5}{3}\sigma_{pm}^2 + 2\sigma_{tr}^2, \tag{A.40}$$

$$cov[\Delta^2 y_{i,T}^{obs}, \Delta^2 y_{i,T+2}^{obs}] = \frac{1}{6}\sigma_{pm}^2 - \sigma_{tr}^2, \tag{A.41}$$

$$cov[\Delta^2 c_{i,T+2}^{obs}, \Delta^2 y_{i,T+2}^{obs}] = \frac{5}{3}\phi\sigma_{pm}^2 + \tau\{2 + \frac{1}{\lambda}(1 - e^{-\lambda})(e^{-2\lambda} - e^{-\lambda} - 2)\}\sigma_{tr}^2, \tag{A.42}$$

$$cov[\Delta^2 c_{i,T}^{obs}, \Delta^2 y_{i,T+2}^{obs}] = \frac{\phi}{6}\sigma_{pm}^2 + \tau\{-1 + \frac{1}{\lambda}(1 - e^{-\lambda})\}\sigma_{tr}^2 \tag{A.43}$$

for $K = 2$.

$$var[\Delta^4 y_{i,T+4}^{obs}] = \frac{11}{3}\sigma_{pm}^2 + 2\sigma_{tr}^2, \tag{A.44}$$

$$cov[\Delta^4 y_{i,T}^{obs}, \Delta^4 y_{i,T+4}^{obs}] = \frac{1}{6}\sigma_{pm}^2 - \sigma_{tr}^2, \tag{A.45}$$

$$cov[\Delta^4 c_{i,T+4}^{obs}, \Delta^4 y_{i,T+4}^{obs}] = \frac{11}{3}\phi\sigma_{pm}^2 + \tau\{2 + \frac{1}{\lambda}(1 - e^{-\lambda})(e^{-4\lambda} - e^{-3\lambda} - 2)\}\sigma_{tr}^2, \tag{A.46}$$

$$cov[\Delta^4 c_{i,T}^{obs}, \Delta^4 y_{i,T+4}^{obs}] = \frac{\phi}{6}\sigma_{pm}^2 + \tau\{-1 + \frac{1}{\lambda}(1 - e^{-\lambda})\}\sigma_{tr}^2 \tag{A.47}$$

for $K = 4$.

To estimate the MPC using these equations, we need to identify τ. To do so, I exploit the following fact: when the real interest rate is close to zero, the cumulative consumption response to a temporary income shock after a long enough time should be equal to the size of the shock itself, *i.e.*,

$$\lim_{t\to\infty} \overrightarrow{\Psi}_t \cdot \frac{E[C]}{E[Y]} = \tau \cdot \frac{E[C]}{E[Y]} \approx 1.$$

Under the assumption that the effective real interest rates for households' consumption-saving problem are close to zero in both Peru and the U.S.[9], I use the following equation to identify τ.

[9] In the real world, the real interest rates in Peru are noticeably higher than those in the U.S. Reflecting this fact will widen the gap between the MPC estimates of the two countries.

$$E[\tau C_{i,t-K} - Y_{i,t-K}] = 0. \tag{A.48}$$

Under the assumption, the MPC after the unit time length ($\Delta t = 1$) becomes

$$MPC = 1 - e^{-\lambda}.$$

For the Peruvian sample, I estimate the quarterly MPC ($= 1 - e^{-\lambda}$) together with σ^2_{pm}, σ^2_{tr}, ϕ, and τ using equations (A.44), (A.45), (A.46), (A.47), and (A.48). For the U.S. sample, I estimate the annual MPC ($= 1 - e^{-\lambda}$) with the other four parameters using equations (A.40), (A.41), (A.42), (A.43), and (A.48). As in the baseline analysis, the estimation is separately conducted for each of the income deciles. The income deciles are constructed by sorting type-3 observations of period $t-K$, t, and $t+K$ by y_{t-K}. For the estimation, I use the GMM method. For comparison between the quarterly MPCs and the annual MPCs, again I convert the Peruvian quarterly MPCs into annual MPCs using Auclert (2019)'s conversion formula (1.16).

Figure A.1j plots the annual MPC estimates of Peru and the U.S. We can see from this figure that the two main patterns – (i) the mean MPC being substantially higher and (ii) within-country MPC heterogeneity over the income distribution being substantially stronger in Peru than in the U.S.– robustly appear in the continuous-time model in which the time aggregation problem does not exist any more.

Case 2. When $(Y^{obs}_{i,T}, C^{obs}_{i,T}) = (\bar{Y}_{i,T}, C_{i,T})$

When $(Y^{obs}_{i,T}, C^{obs}_{i,T}) = (\bar{Y}_{i,T}, C_{i,T})$, we have the following variances and covariances in the discrete-time model.

$$var[\Delta y^{obs}_{i,T}] = \left(\frac{1}{m} + \frac{(m-1)(2m-1)}{3m^2}\right)(m\sigma^2_{pm,m}) + 2\left(\frac{\sigma^2_{tr,m}}{m}\right), \tag{A.49}$$

$$cov[\Delta y^{obs}_{i,T}, \Delta y^{obs}_{i,T+1}] = \frac{m^2-1}{6m^2}(m\sigma^2_{pm,m}) - \left(\frac{\sigma^2_{tr,m}}{m}\right), \tag{A.50}$$

$$cov[\Delta y_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2, \tag{A.51}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T}^{obs}] = \phi \frac{m+1}{2m}(m\sigma_{pm,m}^2) + (3\overrightarrow{\Psi}_{\frac{m-1}{m}} - \overrightarrow{\Psi}_{1+\frac{m-1}{m}})\left(\frac{\sigma_{tr,m}^2}{m}\right), \tag{A.52}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+1}^{obs}] = \phi \frac{m-1}{2m}(m\sigma_{pm,m}^2) - \overrightarrow{\Psi}_{\frac{m-1}{m}}\left(\frac{\sigma_{tr,m}^2}{m}\right), \tag{A.53}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2, \tag{A.54}$$

$$\begin{aligned} cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T-N}^{obs}] = \Big\{&(\overrightarrow{\Psi}_{N+\frac{m-1}{m}} - 2\overrightarrow{\Psi}_{N-1+\frac{m-1}{m}} + \overrightarrow{\Psi}_{N-2+\frac{m-1}{m}}) \\ &- (\overrightarrow{\Psi}_{N+1+\frac{m-1}{m}} - 2\overrightarrow{\Psi}_{N+\frac{m-1}{m}} + \overrightarrow{\Psi}_{N-1+\frac{m-1}{m}})\Big\}\left(\frac{\sigma_{tr,m}^2}{m}\right), \quad N \geq 1. \end{aligned} \tag{A.55}$$

As m approaches infinity satisfying equations (A.28), (A.29), (A.30), and (A.31), the continuous-time model in the limit has the following equations for the variances and covariances.

$$var[\Delta y_{i,T}^{obs}] = \frac{2}{3}\sigma_{pm}^2 + 2\sigma_{tr}^2, \tag{A.56}$$

$$cov[\Delta y_{i,T}^{obs}, \Delta y_{i,T+1}^{obs}] = \frac{1}{6}\sigma_{pm}^2 - \sigma_{tr}^2, \tag{A.57}$$

$$cov[\Delta y_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2, \tag{A.58}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T}^{obs}] = \frac{\phi}{2}\sigma_{pm}^2 + \{2\tau(1-e^{-\lambda}) - \tau e^{-\lambda}(1-e^{-\lambda})\}\sigma_{tr}^2, \tag{A.59}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+1}^{obs}] = \frac{\phi}{2}\sigma_{pm}^2 - \tau(1-e^{-\lambda})\sigma_{tr}^2, \tag{A.60}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2, \tag{A.61}$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T-N}^{obs}] = \{-\tau e^{-\lambda(N-1)}(1-e^{-\lambda})^2 + \tau e^{-\lambda N}(1-e^{-\lambda})^2\}\sigma_{tr}^2, \quad N \geq 1. \tag{A.62}$$

From equations (A.56), (A.57), (A.58), (A.59), (A.60), (A.61), and (A.62), we can obtain the variances and covariances of $\Delta^K c_{i,T}^{obs}$ and $\Delta^K y_{i,T}^{obs}$ for $K = 2$ and $K = 4$ as follows.

$$var[\Delta^2 y_{i,T+2}^{obs}] = \frac{5}{3}\sigma_{pm}^2 + 2\sigma_{tr}^2, \tag{A.63}$$

$$cov[\Delta^2 y^{obs}_{i,T}, \Delta^2 y^{obs}_{i,T+2}] = \frac{1}{6}\sigma^2_{pm} - \sigma^2_{tr}, \tag{A.64}$$

$$cov[\Delta^2 c^{obs}_{i,T+2}, \Delta^2 y^{obs}_{i,T+2}] = \frac{3}{2}\phi\sigma^2_{pm} + \tau(1 - e^{-\lambda})(2 - e^{-2\lambda})\sigma^2_{tr}, \tag{A.65}$$

$$cov[\Delta^2 c^{obs}_{i,T}, \Delta^2 y^{obs}_{i,T+2}] = \frac{\phi}{2}\sigma^2_{pm} - \tau(1 - e^{-\lambda})\sigma^2_{tr} \tag{A.66}$$

for $K = 2$.

$$var[\Delta^4 y^{obs}_{i,T+4}] = \frac{11}{3}\sigma^2_{pm} + 2\sigma^2_{tr}, \tag{A.67}$$

$$cov[\Delta^4 y^{obs}_{i,T}, \Delta^4 y^{obs}_{i,T+4}] = \frac{1}{6}\sigma^2_{pm} - \sigma^2_{tr}, \tag{A.68}$$

$$cov[\Delta^4 c^{obs}_{i,T+4}, \Delta^4 y^{obs}_{i,T+4}] = \frac{7}{2}\phi\sigma^2_{pm} + \tau(1 - e^{-\lambda})(2 - e^{-4\lambda})\sigma^2_{tr}, \tag{A.69}$$

$$cov[\Delta^4 c^{obs}_{i,T}, \Delta^4 y^{obs}_{i,T+4}] = \frac{\phi}{2}\sigma^2_{pm} - \tau(1 - e^{-\lambda})\sigma^2_{tr} \tag{A.70}$$

for $K = 4$.

Under the identification of τ by equation (A.48) as in the first case, I estimate Peruvian households' quarterly MPC ($= 1 - e^{-\lambda}$) together with σ^2_{pm}, σ^2_{tr}, ϕ, and τ using equations (A.67), (A.68), (A.69), (A.70), and (A.48). For the U.S. sample, I estimate annual MPC ($= 1 - e^{-\lambda}$) with the other four parameters using equation (A.63), (A.64), (A.65), (A.66), and (A.48). Again, the estimation is separately conducted for each of the income deciles, and the income deciles are constructed by sorting type-3 observations of period $t - K$, t, and $t + K$ by y_{t-K}. As in the first case, I use the GMM estimation method, and the quarterly MPCs of the Peruvian households are converted into annual MPCs using Auclert (2019)'s conversion formula (1.16).

Figure A.1k plots the annual MPC estimates of Peru and the U.S. This figure verifies that the two main findings – (i) the mean MPC being substantially higher and (ii) within-country MPC heterogeneity over the income distribution being substantially stronger in Peru than in the U.S.– are robust in the continuous-time model in which both the time aggregation problem and the time inconsistency problem with a longer reference period for income than that for consumption are explicitly addressed.

It is noteworthy that the time inconsistency problem with a reference period for income being longer than that for consumption could be more serious in the PSID than in ENAHO. In ENAHO, both the reference periods for income and expense items included in the baseline measures of income and consumption are restricted to be within the previous three months. On the other hand, in the PSID, the reference periods for income items are fixed at a year, while the reference periods for expense items could be as short as a week, depending on the interpretation of the questionnaires. (See the discussion in footnote 19 of the main text.) As another robustness check for the concern that this time inconsistency problem is more serious in the PSID than in ENAHO, we can consider a case in which this time inconsistency problem is present only in the U.S. In this case, the relevant comparison should be between the MPC estimates of Peruvian households in Figure A.1j and those of U.S. households in Figure A.1k. The two main findings robustly appear even in this comparison.

Case 3. When $(Y_{i,T}^{obs}, C_{i,T}^{obs}) = (Y_{i,T}, \bar{C}_{i,T})$

When $(Y_{i,T}^{obs}, C_{i,T}^{obs}) = (Y_{i,T}, \bar{C}_{i,T})$, the discrete-time model has the following equations.

$$cov[\Delta y_{i,T}^{obs}, \Delta y_{i,T+1}^{obs}] = -\sigma_{tr,m}^2,$$

$$cov[\Delta y_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2,$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+1}^{obs}] = -\frac{1}{m}\overrightarrow{\Psi}_0\, \sigma_{tr,m}^2,$$

$$cov[\Delta c_{i,T}^{obs}, \Delta y_{i,T+N}^{obs}] = 0, \quad N \geq 2.$$

From these four equations, we can derive

$$cov[\Delta^K y_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}] = -\sigma_{tr,m}^2, \tag{A.71}$$

$$cov[\Delta^K c_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}] = -\frac{1}{m}\overrightarrow{\Psi}_0\, \sigma_{tr,m}^2. \tag{A.72}$$

for any $K \geq 1$. From equations (A.71) and (A.72), we have

$$MPC = \overrightarrow{\Psi}_1 > \overrightarrow{\Psi}_0 = m \cdot \frac{cov[\Delta^K c_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]}{cov[\Delta^K y_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]}. \tag{A.73}$$

Therefore, when

$$\frac{cov[\Delta^K c_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]}{cov[\Delta^K y_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]} > 0, \tag{A.74}$$

the MPC out of a transitory income shock approaches infinity as m goes to infinity. This conclusion is contradictory to any continuous-time model with finite interest rates. In other words, the continuous-time model with $(Y_{i,T}^{obs}, C_{i,T}^{obs}) = (Y_{i,T}, \bar{C}_{i,T})$ cannot explain data that exhibits inequality (A.74).

However, as long as m is finite and satisfies

$$m \cdot \frac{cov[\Delta^K c_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]}{cov[\Delta^K y_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]} < 1,$$

equation (A.73) is not necessarily inconsistent with the discrete-time model. More importantly, equation (A.73) is helpful to understand the bias caused by the time-inconsistency problem with a longer reference period for consumption. When the true lengths of the reference periods for consumption and income are 1 and $\frac{1}{m}$, respectively, and we falsely treat the length for the reference periods for both income and consumption as 1 in the estimation, there is a time inconsistency problem in such a way that the true reference period for income is shorter than that for consumption. In this situation, we will estimate MPC by $\frac{cov[\Delta^K c_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]}{cov[\Delta^K y_{i,T}^{obs}, \Delta^K y_{i,T+K}^{obs}]}$. As equation (A.73) shows, this is an underestimation.

It is worth noting that the time inconsistency problem with a longer reference period for consumption can be present in the Peruvian sample but not in the U.S. sample, as discussed in footnote 19. In other words, the MPCs of Peruvian households are underestimated, while those of U.S. households are not, if any significant bias is generated by this problem. In this case, correcting this problem will only widen the MPC gap between Peru and the U.S.

A.4.10 Using a Different Age Restriction for Household Heads in the Sample Selection

In the baseline sample selection, I restrict the ages of household heads to be between 25 and 65 in both the Peruvian and U.S. samples. Kaplan et al. (2014b) uses a narrower selection by restricting the ages of household heads to be between 25 and 55. Here, I conduct a robustness check by adopting Kaplan et al. (2014b)'s age restriction (or, equivalently, dropping observations with household heads younger than 25 or older than 55). Figure A.1l plots the result.

A.4.11 Using an Alternative Definition of Income Outliers in the Sample Selection

As discussed in Appendix A.2.3, there is a difference in the definition of income outliers in the Peruvian sample selection and the U.S. sample selection. In the Peruvian sample selection, I define income outliers as households whose income growth is in the range of the extreme 1 percent (0.5 percent at the top and 0.5 percent at the bottom) in the calendar-year sub-samples at least one time. In the U.S. sample selection, I adopt Kaplan et al. (2014b)'s definition of income outliers. They categorize households as income outliers if their nominal income is below 100 Dollars or their income growth is greater than 5 or less than -0.8 at least one time. I do not use this criteria for the Peruvian sample selection because it is not straightforward to determine the right cutoffs for Peruvian households reflecting cross-country differences including the difference in growth units (the two-year-over-two-year growth of annual income for U.S. households, the year-over-year growth of quarterly income for Peruvian households).

Regarding the difference in the definition of outliers, I conduct a robustness check by defining Peruvian income outliers in a more similar fashion with Kaplan et al. (2014b), despite the difficulty of finding the right corresponding cutoffs. Specifically, I categorize Peruvian households as income outliers if their nominal income is below 150 Sols[10] or their income growth is greater than 5 or less than -0.8 at least one time. Figure A.1m plots the MPC estimates under the alternative definition of income outliers in the Peruvian sample selection.

[10]The cutoff of 150 Sols is chosen by reflecting the fact that the 'PPP conversion factor, GDP (LCU per international $)' of World Development Indicators (WDI) varies from 1.34 to 1.56 during 2004-2016.

A.4.12 Selecting Male Heads Only in the Sample Selection

In the baseline sample selection, I include both households with male heads and those with female heads in both the Peruvian and U.S. samples. In this robustness check, I drop households with female heads. Figure A.1n plots the result.

A.4.13 Applying a Stricter Rule in Detecting Potentially Fake Type-2 Observations

In the sample selection for the Peruvian sample, I detect and drop potentially fake type-2 observations, which are likely to connect two different households. As discussed in Appendix A.2.4, I identify them by type-2 observations that do not have any verified same member. In this robustness check, I apply a stricter rule in detecting them at the cost of a smaller sample size as follows: if the number of verified same members of a type-2 observation is less than half of the household size for any of the two households connected as the type-2 observation, I identify it as a potentially fake type-2 observation and drop it. Figure A.1o plots the MPC estimation result under the stricter rule.

A.5 MPC Comparison over the PPP-converted level of income $Y_{i,t}$

In this section, I test a null hypothesis that MPC is a function of the PPP-converted level of income $Y_{i,t}$ (including both predictable and unpredictable components), regardless of whether households live in Peru or in the U.S. To this end, I sort households by $Y_{i,t}$ (instead of $y_{i,t}$) to construct income deciles, estimate MPCs of the deciles, and plot them over the x-axis of the PPP-converted group-average values of $Y_{i,t}$ in Figure A.2.[11] It turns out that the top three deciles in Peru and the bottom three deciles in the U.S. overlap in their PPP-converted income, and in the overlapped region, the MPC estimates of the Peruvian top three deciles are substantially higher than those of the U.S. bottom three deciles. To see if the cross-country MPC gap in the overlapped region is statistically significant, I conduct a two-sided test on the null hypothesis that the mean MPC of the Peruvian top three deciles is equal to that of the U.S. bottom three deciles. As Table

[11] For the PPP conversion, I use WDI's data series, 'PPP conversion factor, GDP (LCU per international $)'.

A.4 reports, the mean MPC of the Peruvian top three deciles (44.2 percent) is significantly different from the mean MPC of the U.S. bottom three deciles (17.3 percent) at the 1% confidence level.

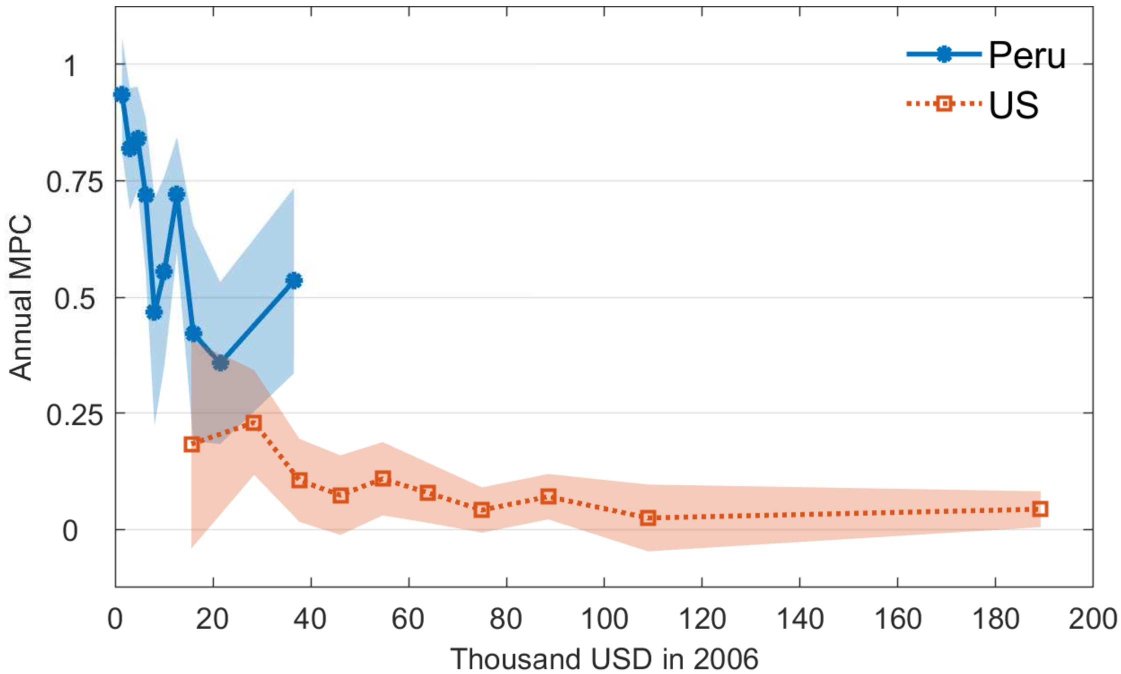


Figure A.2: Annual MPCs of $Y_{i,t}$-deciles on the x-axis of PPP-converted group-average $Y_{i,t}$

Notes: Shaded areas represent 95% confidence intervals.

Table A.4: Mean MPC Comparison in the Overlapped Region

	Peruvian Top Three Deciles	U.S. Bottom Three Deciles
mean MPC	0.442	0.173
	(0.062)	(0.046)
p-value	0.00048	

Notes: The last row of the table reports the p-value of the two-sided test on the null hypothesis that the mean MPC of the top three income($Y_{i,t}$) deciles in Peru is equal to that of the bottom three deciles in the U.S.

Appendix B: Appendix to Chapter 2

B.1 Consumption Growth Rates and Standard Errors in Numerical Values

In this section, I report the numerical values of the consumption growth rates and standard errors plotted in Figure 2.2.

Table B.1: Group Average Consumption Growth Difference against the Top Income Decile

	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Peru	0.302	0.232	0.197	0.168	0.142	0.108	0.097	0.051	0.044	0
	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(n.a.)
N	2,364	2,375	2,309	2,230	2,177	2,080	2,116	2,116	2,134	2,087
U.S.	0.078	0.049	0.048	0.030	0.039	0.035	0.029	0.032	0.027	0
	(0.013)	(0.012)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(n.a.)
N	1,811	1,949	2,031	2,058	2,076	2,091	2,055	1,978	1,938	1,859

Notes: The estimates and the standard errors reported in this table are used to plot Figure 2.2.

B.2 Robustness for the Group Average Consumption Growth Difference against the Top Income Decile

This subsection presents robustness checks for the patterns in the group-average consumption growth difference against the top income decile. Each panel of Figure B.1 plots the consumption growth differences of each robustness check. From the panels in Figure B.1, we can observe that the two main patterns in Figure 2.2 – (i) lower income deciles exhibiting higher consumption growth in both countries and (ii) the first pattern being substantially stronger in Peru than in the U.S. – robustly appear in the following alternative setups.

B.2.1 Including Non-purchased Consumption

As in Appendix A.4.1, I include non-purchased consumption in the measures of consumption in both the Peruvian and U.S. samples. Figure B.1a plots the result.

B.2.2 Restricting Expense Categories to Those Available in the PSID

As in Appendix A.4.2, I exclude clothing, recreation, alcohol, and tobacco from the consumption of Peruvian households. Figure B.1b plots the result.

B.2.3 Excluding Expense Items from Income

As in Appendix A.4.4, I exclude rental equivalence of housing provided by work and rental equivalence of donated housing from the income of Peruvian households. In principle, this change of income definition can affect the group-average consumption growth by changing the income quantiles of the households. Figure B.1c plots the result.

B.2.4 Sorting Income ($y_{i,t}$) in Different Observation Pools

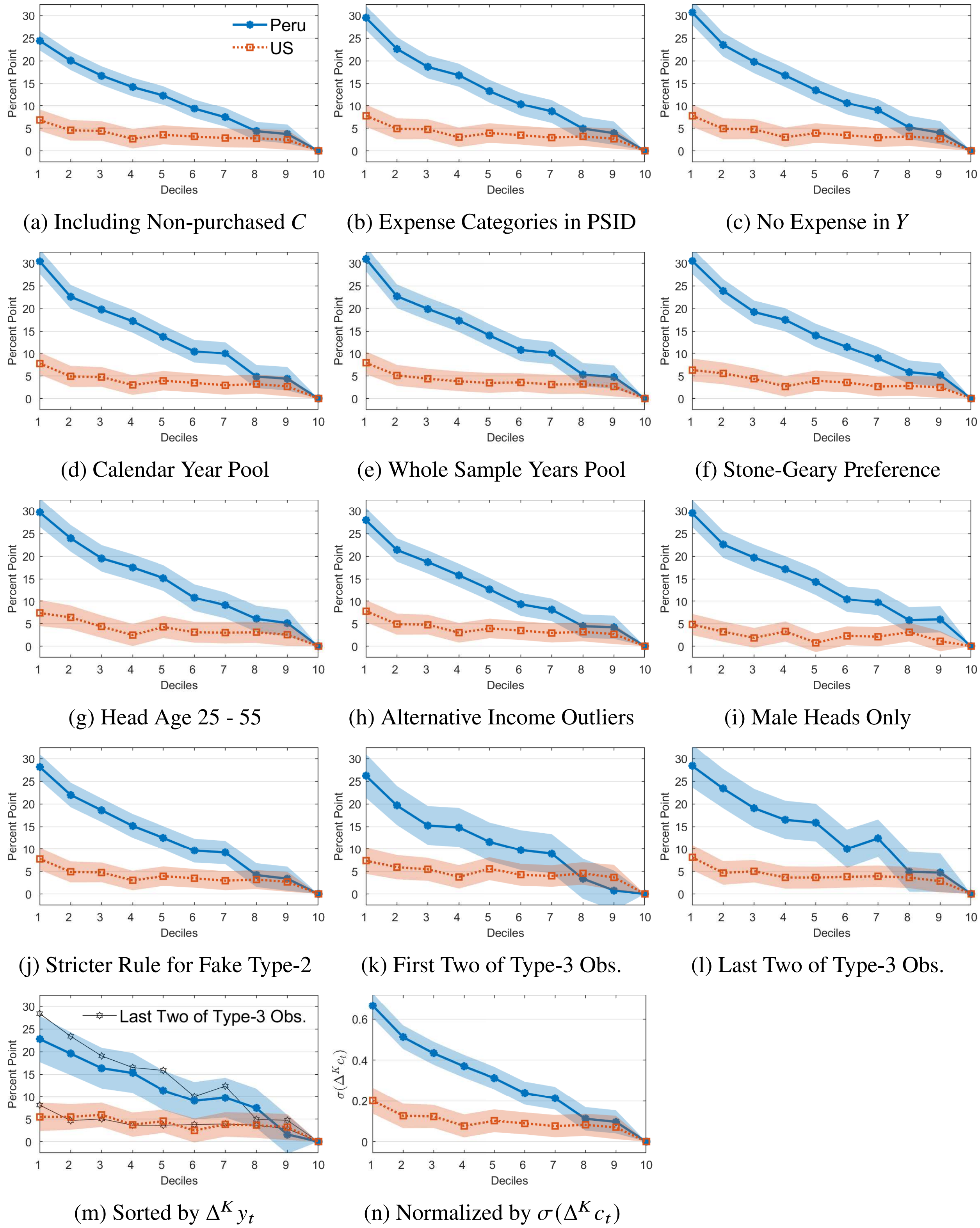
As in Appendix A.4.5, I sort income in different observation pools from the baseline analysis, including (i) the pool of each calendar year (not only for the U.S. sample, but also for the Peruvian sample), and (ii) the pool of the whole sample years. Figure B.1d and Figure B.1e plot the results under the pool of each calendar year and the pool of the whole sample years, respectively.

B.2.5 Incorporating a Subsistence Point into the Preference

As in Appendix A.4.7, I incorporate the subsistence point in the form of Stone-Geary preference into the model. Figure B.1f plots the result.

B.2.6 Using a Different Age Restriction for Household Heads in the Sample Selection

As in Appendix A.4.10, I change the age restriction from 25 - 65 to 25-55 in the sample selection for both the Peruvian and U.S. samples. Figure B.1g plots the result.



(a) Including Non-purchased C
(b) Expense Categories in PSID
(c) No Expense in Y
(d) Calendar Year Pool
(e) Whole Sample Years Pool
(f) Stone-Geary Preference
(g) Head Age 25 - 55
(h) Alternative Income Outliers
(i) Male Heads Only
(j) Stricter Rule for Fake Type-2
(k) First Two of Type-3 Obs.
(l) Last Two of Type-3 Obs.
(m) Sorted by $\Delta^K y_t$
(n) Normalized by $\sigma(\Delta^K c_t)$

Figure B.1: Robustness – Group-average Consumption Growth Difference against the Top Income Decile

Notes: In the x-axis of each panel, 1 is the bottom decile. Shaded areas represent 95% confidence intervals.

B.2.7 Using an Alternative Definition of Income Outliers in the Sample Selection

In this robustness check, I use the alternative definition of income outliers for the Peruvian sample selection discussed in Appendix A.4.11. Figure B.1h plots the result.

B.2.8 Selecting Male Heads Only in the Sample Selection

As in Appendix A.4.12, I drop households with female heads in both the Peruvian and U.S. samples. Figure B.1i plots the result.

B.2.9 Applying a Stricter Rule in Detecting Potentially Fake Type-2 Observations

As in Appendix A.4.13, I apply the stricter rule in detecting potentially fake type-2 observations in the sample selection for the Peruvian sample. Figure B.1j plots the result.

B.2.10 Using Type-3 Observations Only

In the main text, the analysis of comparing group-average consumption growth of the income deciles against the top decile uses type-2 observations, while the MPC estimation uses type-3 observations. As a consequence, the former uses a far larger number of observations than the latter. The larger number of observations in the consumption growth comparison improves the precision of the estimates but can also cause a concern of not using the same set of observations as the MPC estimation. To resolve this concern, I conduct the consumption growth comparison using only the type-3 observations that are used in the MPC estimation. Specifically, a type-3 observation of household i in $t-K$, t, and $t+K$ is sorted by its unpredictable component of income in period $t-K$, and the consumption growth $\Delta^K c_{i,t}$ is used for the group-average consumption growth comparison. Figure B.1k plots the result. Although the confidence intervals are wider than Figure 2.2 due to a smaller sample size, we can robustly observe the two main patterns – (i) lower income deciles exhibiting higher consumption growth in both countries and (ii) the first pattern being substantially stronger in Peru than in the U.S.

Each type-3 observation includes two type-2 observations: the first two and last two survey responses. In Figure B.1k, I use the former type-2 observation of each type-3 observation. In Figure B.1l, I instead use the latter type-2 observation of each type-3 observation. Specifically, when a type-3 observation is composed of a household's survey responses in period $t-K$, t, and $t+K$, I sort it by its unpredictable component of income in period t, and the consumption growth $\Delta^K c_{i,t+K}$ is used for the group-average consumption growth comparison. Again, the confidence intervals are wider than Figure 2.2, but we can robustly observe the two main patterns.

B.2.11 Sorting Observations with $\Delta^K y_{i,t}$

As discussed in subsection 2.2, households with lower income are more likely to be constrained because they are more likely to have received negative transitory income shocks and want to run down their asset position. If this is indeed the main reason why we observe the two main patterns – (i) lower income deciles exhibiting higher consumption growth in both countries and (ii) the first pattern being substantially stronger in Peru – in Figure 2.2, we should observe the same patterns when we group observations based on income growth $\Delta^K y_{i,t}$ instead of income level $y_{i,t}$ because the income growth also includes temporary income shock $\epsilon_{i,t}$, as seen in equation (1.9). To verify whether it is the case, I group type-3 observations of household i appearing in period $t-K$, t, and $t+K$ using income growth $\Delta^K y_{i,t}$, and compare the group averages of consumption growth $\Delta^K c_{i,t+K}$. Figure B.1m plots the result. The two main patterns of Figure 2.2 robustly appear in this figure.

For the comparison between the income growth grouping and the income level grouping, the right point of comparison against Figure B.1m is Figure B.1l. This is because both figures use the consumption growth of the second type-2 observation of each type-3 observation (*i.e.*, $\Delta^K c_{i,t+K}$ for each type-3 observation of period $t-K$, t, and $t+K$) and the only difference between the two figures is that one figure groups observations by $\Delta^K y_t$, while the other one groups them by y_t. For the sake of comparison, I plot the point estimates of Figure B.1l in Figure B.1m as black thin lines with star markers. As the comparison shows, the degree of within-country heterogeneity in the consumption growth under the income growth grouping is similar to that under the income level grouping in both countries.

B.2.12 Normalizing the Consumption Growth Differences with Standard Deviations

We observe the year-over-year growth of quarterly consumption in the Peruvian sample and the two-year-over-two-year growth of annual consumption in the U.S. sample. Despite this difference in growth units, in Figure 2.2, I plot the graphs of both countries for the consumption growth differences against the top income decile in percent points and make visual comparison. This comparison is justifiable because the standard deviation of the observed consumption growth in the Peruvian sample (45.3 percent) is in the same ballpark as the standard deviation in the U.S. sample (38.7 percent). To illustrate this point, I plot the consumption growth differences in the unit of the standard deviation in Figure B.1n. The graphs in this figure do not look much different from those in Figure 2.2, and the two main patterns – (i) lower income deciles exhibiting higher consumption growth and (ii) the first pattern being substantially stronger in Peru than in the U.S.– robustly appear in this figure.

B.3 The Advantage of Income Grouping in Detecting Liquidity Constraints

I use income deciles to split the sample into groups. The income measure I use to construct the income deciles is the unpredictable (by observable characteristics) component of labor income and transfers. As discussed in subsection 2.2, the standard incomplete-market precautionary-saving models predict that this income grouping can pick up the effect of liquidity constraints since lower-income households are more likely to be constrained than higher-income households. This paper is not the first to exploit this fact. For example, Zeldes (1989) tests for the presence of liquidity constraints for groups of households using lagged income as an instrument.

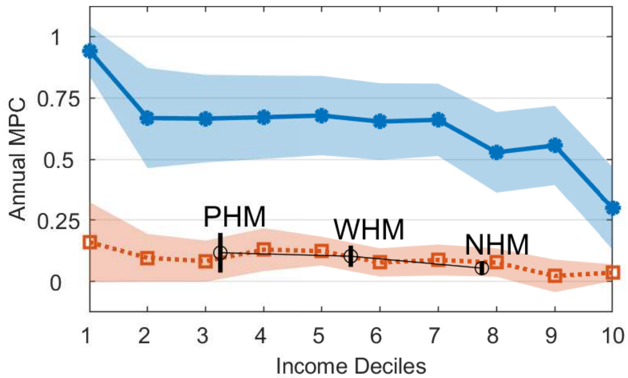
In the literature, wealth grouping or liquid-wealth grouping are more common grouping strategies for the identification of households that are at or close to liquidity constraints. For example, Zeldes (1989) uses net worth to split the sample into groups. Kaplan et al. (2014b) focus on households that hold little liquid wealth. In particular, they emphasize the existence of wealthy hand-to-mouth households, who are wealthy in illiquid assets but hold little liquid wealth, and find that their consumption response to transitory income shocks is as sensitive as that of poor hand-to-mouth households, who are poor in both illiquid and liquid assets.

Admittedly, I choose income grouping because wealth grouping or liquid-wealth grouping are not available for the Peruvian sample, as ENAHO does not collect detailed information on wealth. However, it is also noteworthy that the income grouping I use in this paper might have an advantage in detecting the effect of liquidity constraints compared to wealth grouping or liquid-wealth grouping. As Aguiar et al. (2019) point out, low-wealth or low-liquid-wealth households may exhibit high MPC not because they are at or close to liquidity constraints but because they have preferences for low wealth targets. If preference heterogeneity is allowed in the standard incomplete-market precautionary-saving models, households with a low degree of patience (β_i) or a high degree of IES ($1/\sigma_i$) will have low wealth targets because they front-load consumption. At the same time, they would exhibit high MPC even in the absence of liquidity constraints exactly because of their front-loading behavior.

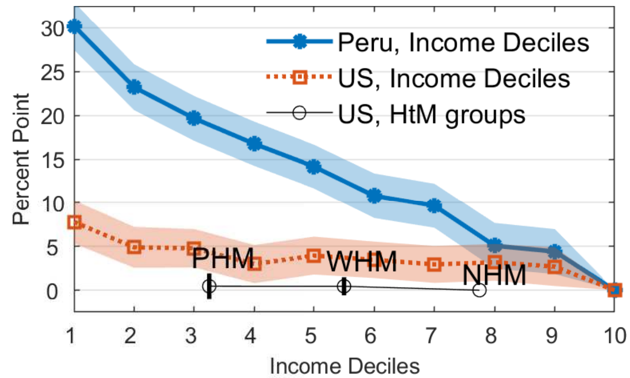
In supporting their argument that wealth-poor or liquid-wealth-poor households are not necessarily at or close to liquidity constraints, Aguiar et al. (2019) show that the average consumption growth of U.S. hand-to-mouth households is not greater than that of non-hand-to-mouth households. To see if this is also the case in the U.S. sample I use in this paper, I repeat the analyses of subsection 1.4.1 and 2.2 but using the U.S. hand-to-mouth groups. In doing so, I adopt Kaplan et al. (2014b)'s definition of poor-hand-to-mouth (PHM), wealthy-hand-to-mouth (WHM), and non-hand-to-mouth (NHM) households and use the identifiers of these groups included in their dataset.

Figure B.2a plots the annual MPC estimates for the U.S. PHM, WHM, and NHM groups. For the sake of comparison, Figure B.2a also plots the MPC estimates for the U.S. income deciles and the Peruvian income deciles presented in Figure 1.1.

Two patterns are worth noting from Figure B.2a. First, as Kaplan et al. (2014b) highlight,



(a) Annual MPCs



(b) Average Consumption Growth Differences

Figure B.2: Comparison with U.S. Hand-to-Mouth Groups

Notes: Figure B.2a plots the annual MPCs of the poor hand-to-mouth (PHM), wealthy hand-to-mouth (WHM), and non-hand-to-mouth (NHM) groups defined in Kaplan et al. (2014b) on top of Figure 1.1. The unfilled circle markers represent the point estimates for these groups, and the vertical lines passing the markers represent 95% confidence intervals. Figure B.2b plots the difference between the group-average consumption growth of PHM and WHM against that of NHM on top of Figure 2.2.

the consumption of PHM and WHM households responds more sensitively to transitory income shocks than that of NHM households in their dataset. The annual MPCs of PHM (11.7 percent) and WHM (10.3 percent) are approximately twice as large as that of NHM (5.4 percent).[1] Second, even when compared with PHM and WHM in the U.S., the MPCs of Peruvian income deciles are substantially higher.

Figure B.2b plots the difference between the average consumption growth in the following period of PHM and WHM against that of NHM. For the sake of comparison, Figure B.2b also plots the difference between the average consumption growth of the income deciles against that of the top income decile in Peru and the U.S. presented in Figure 2.2.

In accordance with Aguiar et al. (2019)'s finding, Figure B.2b shows that the following-period consumption growth of PHM households and that of WHM households are not significantly greater than that of NHM households in Kaplan et al. (2014b)'s dataset. This result suggests that PHM and WHM households might not necessarily be more constrained than NHM households in the U.S.

[1]The annual MPC estimates I report here are different from the numbers reported in Kaplan et al. (2014b) for the following reasons. First, they report estimates on Blundell et al. (2008)'s partial insurance parameter ψ, while I compute MPC by multiplying ψ with the consumption-output ratio. Second, I revise their consumption measure and sample selection procedure as discussed in section 1.3.

In contrast, under the income grouping, we can observe clear patterns in the same U.S. sample that lower income deciles tend to exhibit higher consumption growth and all the other nine deciles exhibit significantly greater consumption growth than the top income decile. This result suggests that unlike the wealth grouping, the income grouping used in this paper successfully picks up the effect of liquidity constraints.

Theoretically, this outcome may arise because labor income and transfers are less affected by preference heterogeneity than wealth. For example, when preference heterogeneity is introduced into the standard models in such a way that it is independent of the labor income process and transfers (which is a common assumption in such models with preference heterogeneity), preference heterogeneity affects individual wealth levels by changing the target wealth, while it does not affect individual levels of labor income and transfers.

Appendix C: Appendix to Chapter 3

C.1 Details on MPC Estimation

C.1.1 Method

The method I use in this paper to estimate MPCs out of transitory income shocks is an extended version of Blundell et al. (2008). Let the individual labor income $Y_{i,t}$ be specified as follows.

$$\log Y_{i,t} = Z'_{i,t}\varphi_t + P_{i,t} + \epsilon_{i,t},$$

$$P_{i,t} = \rho P_{i,t-1} + \zeta_{i,t},$$

$$\zeta_{i,t} \sim_{iid} (0, \sigma^2_{ps}), \quad \epsilon_{i,t} \sim_{iid} (0, \sigma^2_{tr}), \quad \text{and} \quad (\zeta_{i,t})_t \perp (\epsilon_{i,t})_t$$

in which $(x_t)_t$ represents time series $(\cdots, x_{t-2}, x_{t-1}, x_t, x_{t+1}, x_{t+2}, \cdots)$. $Z_{i,t}$ denotes a vector of dummy variables for observable characteristics of household i.[1]

Let ψ_G be Blundell et al. (2008)'s partial insurance parameter to transitory income shocks for group G, which is defined as follows.

$$\psi_G = \frac{cov[\Delta c_{i,t}, \epsilon_{i,t} | (i,t) \in G]}{cov[\Delta y_{i,t}, \epsilon_{i,t} | (i,t) \in G]}$$

in which $c_{i,t}$ and $y_{i,t}$ are the log consumption and log income after controlling for the observable characteristics. (By definition, $y_{i,t} = \log Y_{i,t} - Z'_{i,t}\varphi_t = P_{i,t} + \epsilon_{i,t}$.) In other words, parameter ψ_G is the elasticity of consumption with respect to income when the income change is caused

[1]The observable characteristics of households include education, ethnicity, employment status, region, cohort, household size, number of children, urban area, the existence of members other than heads and spouses earning income, and the existence of persons who do not live with but are financially supported by the household. Among these characteristics, education, ethnicity, employment status, and region are allowed to have time-varying effects.

by a transitory income shock. We can obtain the estimate of ψ_G following Kaplan and Violante (2010)'s identification strategy for Blundell et al. (2008)'s partial insurance parameters under the 'AR(1)+I.I.D.' specification of the income process as follows. Let $\tilde{\Delta}^K y_{i,t}$ and $\Delta^K c_{i,t}$ be

$$\tilde{\Delta}^K y_{i,t} := y_{i,t} - \rho^K y_{i,t-K}, \quad K \geq 1, \quad \text{and}$$

$$\Delta^K c_{i,t} := c_{i,t} - c_{i,t-K}, \quad K \geq 1.$$

Then, we have

$$\tilde{\Delta}^K y_{i,t} = \sum_{s=0}^{K-1} \rho^s \zeta_{i,t-s} + \epsilon_{i,t} - \rho^K \epsilon_{i,t-K}.$$

When the grouping of observation (i,t) is independent of $(\zeta_{i,t+j}, \epsilon_{i,t+j})_{j\geq 0}$ and $\Delta c_{i,t}$ is independent of $(\zeta_{i,t+j}, \epsilon_{i,t+j})_{j\geq 1}$, we can derive

$$\psi_G = \frac{cov[\Delta^K c_{i,t}, \tilde{\Delta}^K y_{i,t+K} | (i,t) \in G]}{cov[\tilde{\Delta}^K y_{i,t}, \tilde{\Delta}^K y_{i,t+K} | (i,t) \in G]}. \tag{C.1}$$

To identify ψ_G using equation (C.1), we need the value of ρ. Adopting Floden and Lindé (2001)'s identification strategy, parameter ρ is estimated using the autocovariance moments of $y_{i,t}$ as follows.[2]

$$E[y_{i,t}^2] = \frac{\sigma_{ps}^2}{1-\rho^2} + \sigma_{tr}^2,$$

$$E[y_{i,t}, y_{i,t+nK}] = \frac{\sigma_{ps}^2}{1-\rho^2} \rho^{nK}, \quad n \geq 1.$$

Once ρ is estimated, I estimate ψ_G using equation (C.1). Since ψ_G is an elasticity, I obtain the MPC estimate by multiplying ψ_G with the consumption-to-income ratio as follows.

$$MPC_G = \psi_G \frac{E[C_{i,t-K} | (i,t) \in G]}{E[Y_{i,t-K} | (i,t) \in G]}.$$

As discussed in section 3.2, ENAHO provides year-over-year growth of quarterly income and

[2] In this estimation, I obtain the estimates of ρ, σ_{ps}, and σ_{tr}. I also use these estimates in calibrating the idiosyncratic labor productivity process in the model of this paper in subsection 3.4.1.

consumption. Therefore, I set one period as a quarter and $K = 4$ for the Peruvian sample. As a result of estimation, I obtain the quarterly MPCs of Peruvian households. On the other hand, the PSID provides two-year-over-two-year growth of annual income and consumption. Thus, I set one period as a year and $K = 2$ for the U.S. sample. As a result of estimation, I obtain the annual MPCs of U.S. households.

C.1.2 Revisions on the MPC estimation procedure of chapter 1

In section 3.2, I make three revisions to the MPC estimation procedure of chapter 1 that are necessary to use the MPC estimates in disciplining the model presented in this paper. First, I change the consumption measure from non-durable consumption to total consumption (including both non-durable consumption and durable consumption). When taking the model to data in section 3.4, after the model is calibrated by targeting the MPC estimates, aggregate shock processes (together with a few other model parameters) are Bayesian-estimated using macro data. In this step, I use total consumption series (as most studies in the literature of emerging market business cycles do) because non-durable consumption series is not available in Peruvian national accounts. To make the consumption concept consistent between micro and macro data, I use the total consumption measure when analyzing the micro data, too. Second, I change the sample periods for both ENAHO and the PSID because some of the key durable expenses are available only after certain years in both surveys. Specifically, I use the 2011-2018 waves of ENAHO and the 2005-2017 waves of the PSID.[3] Third, the income process specification is revised to be consistent with the

[3]My ENAHO sample starts from 2011 because of the following reason. ENAHO is conducted continuously (*i.e.*, households are interviewed in different months) and the reference periods of income and expense items are usually in the format of a specified period before the interview (such as 'previous *n* months') rather than a fixed calender period (such as 'during 2014'). Naturally, I set the reference periods of the consumption and income measures in the same format (*i.e.*, a specified period before the interview such as 'previous *n* months'). One exception is Questionnaire 612. This questionnaire collects information on household furnishings, equipment, and vehicles, which take a sizable portion of durable goods. Until 2010, this questionnaire asks which calendar year each item is acquired, and thus it is not possible to aggregate this questionnaire's expense items with other expense items under a consistent reference period format. From 2011 onward, Questionnaire 612 asks the acquisition month instead of the acquisition year, which makes it possible to recover this questionnaire's expense items during a specified period before the interview (such as 'previous *n* months') and to aggregate these expense items with other expense items under a consistent reference period format. My PSID sample starts from 2005 because the survey began to collect expenses on household furnishings and equipment since then. Moreover, some non-durable items including clothing and recreation are also collected from 2005 onward.

model in this paper. Blundell et al. (2008)'s estimation method requires the structural specification of the income process. In the baseline estimation of chapter 1, the income process is specified as the sum of a permanent component and a transitory component in which the permanent component follows a random walk, as in the original specification of Blundell et al. (2008). In this paper, I instead specify the income process as the sum of a persistent (but not permanent) component and a transitory component by replacing the random walk component with an AR(1) process so that the income process used in the empirical estimation is consistent with the model in this paper.[4]

C.1.3 Reference Periods

In ENAHO, the reference periods are not equal across income and expense items. Typically, expenses or incomes that occur less frequently tend to have longer reference periods. More importantly, households report most items (97.7% of income items, 92.9% of expense items, on average) with reference periods no longer than the previous three months. Given this feature of the data, I set the reference period of consumption and income measures as the previous three months. In aggregating items to construct income and consumption, items with different reference periods than the previous three months are scaled to three-month expenses or incomes. (For example, monthly tobacco expenses are scaled up to three-month expenses by multiplying by three.) Moreover, in order to remove any comovement between income and consumption generated by income shocks prior to the previous three months, I exclude income items with reference periods longer than the previous three months in constructing income.

In the PSID, the reference periods of incomes are firmly fixed to a calendar year. However, the reference periods of expense items can depend on interpretation, as Crawley (2019) points out. For example, food expenses in the PSID can be interpreted either as the last week's expense or the average weekly expense during the calendar year. I adopt the latter interpretation as many other studies do, and treat the reference periods of expense items as being synchronized with those of income items. Naturally, I set the reference period of consumption and income measures as the

[4] I also use this income process specification in one of the robustness checks of chapter 1 in Appendix A.4.6.

corresponding calender year.

As discussed in section 3.2, ENAHO is conducted annually, and I use the 2011-2018 waves. This ENAHO sample provides seven years of year-over-year growth of quarterly income and consumption. For the PSID, I use the 2005-2017 waves, and the survey is conducted biannually during the sample period. This PSID sample provides six years of two-year-over-two-year growth of annual income and consumption.

C.1.4 Variable Construction

The consumption measure used in the MPC estimation is total consumption, which includes both non-durable consumption and durable consumption. To this end, I aggregate the following expenses in each of ENAHO and the PSID: non-durable expenses including 1) food, 2) clothing (including clothing services, footwear, watches and jewelry), 3) housing rent, rental equivalence of owned or donated housing, 4) utilities (heat, electricity, water, etc.), 5) telephone and cable, 6) vehicle repairs and maintenance, 7) gasoline and oil, 8) parking, 9) public transportation, 10) household repairs and maintenance, 11) recreation, 12) insurance (home insurance, car insurance, health insurance, etc.), 13) childcare, 14) domestic services and other home services, 15) personal care, 16) alcohol, 17) tobacco, and 18) daily non-durables (laundry items, bathroom items, matches, candle, stationeries, etc.), and durable expenses including 19) vehicles, 20) furnishings and equipment (textiles, furniture, floor coverings, appliances, housewares, etc.), 21) health, and 22) education.[5] Among the listed expenses, ENAHO does not have expenses on 13) childcare, and the PSID does not have expenses on 14) domestic services and other home services, 15) personal care, 16) alcohol, 17) tobacco, and 18) daily non-durables (laundry items, bathroom items, matches, candle, stationeries, etc.).

For both ENAHO and the PSID, the income measure used in the MPC estimation is the sum of disposable labor income and transfers, as in Blundell et al. (2008). Capital income is excluded in

[5]In listing the expenses, I categorize expenses on 21) health and 22) education as durable expenses because of their durable nature. In national accounts, however, they are categorized as non-durable consumption. Since I use total consumption, whether these expenses are categorized as durable expenses or non-durable expenses do not have any effect.

order not to falsely attribute endogenous capital income changes as income shocks. In ENAHO, capital income and labor income are not distinguishable in self-employment income. As in Diaz-Gimenez et al. (1997), Krueger and Perri (2006), and my chapter 1, I split the self-employment income into labor income part and capital income part using the ratio between unambiguous capital income and unambiguous labor income in the sample.[6] In ENAHO, there are a small fraction of income items that have reference periods longer than the previous three months. As discussed in subsection C.1.3, I exclude them from the income measure. In the PSID, I closely follow Kaplan et al. (2014b) in constructing disposable labor income and transfers. Specifically, disposable labor income and transfers are constructed by i) estimating federal income taxes for total income (including both the component of labor income and transfers and the component of capital income) by TAXSIM program, ii) allocating federal taxes for the component of labor income and transfers using the ratio between this component and the component of capital income in the total income, and iii) subtracting the estimated federal taxes for labor income and transfers from gross labor income and transfers.

For both ENAHO and the PSID, consumption and income are deflated using CPI series. Unlike the reference periods in the PSID sample, the reference periods in the ENAHO sample are not fixed to a calendar period. For example, the three-month window of the reference periods for households surveyed in January, 2015 is one-month earlier than the three-month window for households surveyed in February, 2015. Fortunately, this data feature does not complicate the deflation procedure because ENAHO provides within-year-deflated values for income and expense items. For example, the within-year-deflated values of the food expenses spent on July 2018 are expressed in terms of the 2018 price level. Using these within-year-deflated values, I construct real income and consumption of the ENAHO sample as follows. I first aggregate the within-year-deflated values of income and expense items to construct the within-year-deflated income and consumption measures. Then, I deflate these within-year-deflated income and consumption measures using annual

[6]In the ENAHO sample, the ratio of $\frac{\text{(unambiguous labor income)}}{\text{(unambiguous labor income)+(unambiguous capital income)}}$ is 0.817. This ratio is close to the ratio that Diaz-Gimenez et al. (1997) and Krueger and Perri (2006) use for their U.S. sample, 0.864.

CPI series.

C.1.5 Sample Selection

The sample selection procedure closely follows chapter 1. To describe the procedure, it is convenient to distinguish different units of observations. Let type-n observation be an observation of a household over n consecutive periods. For example, if a household appears three consecutive times in the sample, we obtain three type-1 observations, two type-2 observations, and one type-3 observation associated with this household. Note that observation (i, t) in the MPC estimation procedure described in Appendix C.1.1 represents a type-3 observation, as it is composed of observations on income and consumption of household i in period $t - K$, t, and $t + K$.

Each of the sample selection criteria is applied to either type-1 or type-2 observations. When a type-1 observation is dropped, any type-2 and type-3 observations containing the dropped type-1 observation are dropped. When a type-2 observation is dropped, any type-1 observations that do not belong to any other type-2 observation are dropped, and any type-3 observations that contain the dropped type-2 observations are dropped.

In ENAHO, the sample selection proceeds as follows. First, type-1 observations are dropped if they do not belong to any type-2 observation. Second, type-2 observations that have at least one of the following problems are dropped: i) the interview months are not matched between the two consecutive surveys, ii) the observations are likely to falsely connect two different households[7], or iii) the head of the household changed between the two consecutive surveys. Third, type-1 observations are dropped if the interviews are categorized as 'incomplete' by pollsters. Fourth, type-1 observations are dropped if household heads are younger than 25 or older than 65. Fifth, type-1 observations are dropped if any of the household characteristics in $Z_{i,t}$ are missing. Sixth, type-1 observations are dropped when consumption or income are non-positive. Seventh, type-1 observa-

[7]In ENAHO, panel households are selected based on addresses. The risk of falsely connecting two different households exists when an old household moves out and a new household moves in to a selected address. Type-2 observations subject to this risk, which is defined as 'potentially fake type-2 observations' in chapter 1, can be effectively detected and dropped by checking the household-member-level match between the two consecutive periods. For detailed discussion on why this problem exists and how to detect the potentially fake type-2 observations, see Appendix A.2.4.

tions are dropped when they have too much value in income items with reference periods longer than the previous three months, or more specifically, when (income items with reference periods longer than the previous three months)/((baseline income measure)+(income items with reference periods longer than the previous three months)) is greater than 5%. Eighth, type-1 observations are dropped when households are categorized as income outliers. Households are categorized as income outliers if their income growth falls into the range of extreme 1% (0.5% at the top, 0.5% at the bottom) in calendar-year subsamples at least one time. As a result of the sample selection, I obtain 40,677 type-1 observations, 22,936 type-2 observations, and 9,906 type-3 observations. Panel A of Table C.1 reports the selected observations in each step of the sample selection in ENAHO.

The sample selection in the PSID proceeds similarly to the sample selection in ENAHO as follows. First, type-1 observations are dropped if they do not belong to any type-2 observation with

Table C.1: Sample Selection

	type-1	type-2	type-3
A. ENAHO			
type-1 obs. not belonging to any type-2 obs.	87,305	59,691	32,077
months not matched, fake type-2 obs., or head changed	73,248	47,950	22,652
incomplete survey	63,410	38,343	17,386
age restriction, 25-65	48,636	28,983	12,971
observable characteristics missing	48,403	28,904	12,955
non-positive Y and C	48,144	28,613	12,788
too much 3ml in Y	41,357	23,397	10,154
outliers on income growth	40,677	22,936	9,906
B. The PSID			
type-1 obs. not belonging to any type-2 obs. with a continued head	57,560	45,553	33,546
SEO sample 1968 and Latino sample 1990/1992	39,660	31,523	23,386
topcoded obs.	39,650	31,507	23,369
age restriction, 25-65	31,447	24,380	17,711
observable characteristics missing	30,225	23,277	16,805
non-positive Y and C	30,028	23,021	16570
outliers on income growth	29,145	22,345	16,092

Notes: In the penultimate line of panel A, '3ml' is an abbreviation for 'items with reference periods longer than the previous three months'.

a continued household head. Second, I drop type-1 observations if they belong to the sample from Survey of Economic Opportunities (SEO) (added to the PSID in 1968) or to the Latino sample (added to the PSID in 1990 and 1992). Third, I drop type-1 observations if they have topcoded values in income or expense items. Fourth, type-1 observations are dropped if household heads are younger than 25 or older than 65. Fifth, type-1 observations are dropped if any of the household characteristics in $Z_{i,t}$ are missing. Sixth, type-1 observations are dropped when income or consumption are non-positive. Seventh, type-1 observations are dropped when households are categorized as income outliers. The definition of income outliers is the same as in the ENAHO sample selection. Through this sample selection, I obtain 29,145 type-1 observations, 22,345 type-2 observations, and 16,092 type-3 observations. Panel B of Table C.1 reports the selected observations in each step of the sample selection in the PSID.

C.1.6 Labor Income Grouping

As discussed in section 3.2, I group observation (i,t)s into labor income deciles and estimate the MPCs of each decile. The labor income deciles are constructed as follows. In the estimation procedure described in Appendix C.1.1, observation (i,t) is composed of household i's income and consumption in period $t-K$, t, and $t+K$. These observation (i,t)s are sorted with the unpredictable component of labor income in period $t-K$, $y_{i,t-K}$.[8] Specifically, in accordance with the time unit of each survey (a quarter for ENAHO, a year for the PSID), observations are sorted within a calender quarter subsample in ENAHO and within a calendar year subsample in the PSID. Survey weights are taken into account when computing the quantiles of the sorted observations.

As discussed in subsection C.1.4, the income measure of Peruvian households does not include income items with reference periods longer than the previous three months. Moreover, observations having too much value in this component are dropped in the sample selection, as discussed in subsection C.1.5. If the share of this component in the household income is correlated with the income level, this sample selection can create a selection bias. To resolve this concern, I follow

[8] Because observations are sorted by $y_{i,t-K}$, the grouping of observation (i,t)s is independent of $(\zeta_{i,t+j}, \epsilon_{i,t+j})_{j\geq 0}$, which is a necessary condition for the identification equation (C.1).

chapter 1's approach as follows. When sorting observations and computing their quantiles, I include dropped observations due to having too much value in income items with reference periods longer than the previous three months. When sorting the selected observations together with the dropped observations, I use the unpredictable component of a comprehensive income that includes not only the baseline income measure but also the income items with reference periods longer than the previous three months. The income items with reference periods longer than the previous three months are bad because it generates comovement between income and consumption caused by income shocks prior to the previous three months. However, they are helpful in determining where the selected observations are located in the income distribution.

C.2 Details on How to Solve the Model

C.2.1 Equilibrium under Deterministic Paths of Aggregate Exogenous Variables

In this subsection, I characterize the equilibrium when the economy is subject to deterministic paths of $\{z_t, g_t, \mu_t, \eta_t, \nu_t\}_{t=0}^{\infty}$.

C.2.1.1 Households

Under deterministic paths of $\{z_t, g_t, \mu_t, \eta_t, \nu_t\}_{t=0}^{\infty}$, households' optimization problem can be expressed as the following Bellman equation.

$$V_t(e_1, e_2, b_-, a_-) = \max_{c,b,a} \frac{c^{1-\gamma}}{1-\gamma} + \beta \sum_{e_1', e_2'} P(e_1', e_2' | e_1, e_2) V_{t+1}(e_1', e_2', b, a)$$

$$s.t.$$

$$c + b + a + \eta_t \chi_t(a - (1 + r_t^a)a_-, a_-) = w_t e \bar{l}_t + (1 - \xi)(1 + r_t^b)b_- + (1 + r_t^a)a_-,$$

$$a \geq 0, \quad b \geq 0, \quad \text{and}$$

$$\log e = \log e_1 + \log e_2.$$

On the balanced growth path in which $\{z_t, g_t, \mu_t, \eta_t, \nu_t\}_{t=0}^{\infty}$ are constant at their long-run average values, $V_t,\ t \geq 0$ grows with the rate of $(g^*)^{1-\gamma}$ (or equivalently, $V_{t+1} = (g^*)^{1-\gamma} V_t$).

Given the parametrization of $\chi_t(v, a_-)$ in the main text, its first-order derivatives are

$$\chi_{1,t}(v, a_-) = sign(v)\ \chi_1 \chi_2 \left| \frac{v}{(1 + r_t^a)a_- + \chi_0 X_{t-1}} \right|^{\chi_2 - 1} \quad \text{and}$$

$$\chi_{2,t}(v, a_-) = \chi_1 (1 - \chi_2) \left| \frac{v}{(1 + r_t^a)a_- + \chi_0 X_{t-1}} \right|^{\chi_2} (1 + r_t^a).$$

Both $\chi_{1,t}(v, a_-)$ and $\chi_{2,t}(v, a_-)$ are continuous everywhere, including the area around $v = 0$. Therefore, $\chi_t(v, a_-)$ is continuous and differentiable everywhere.

The optimality conditions of the households' problem can be derived as follows.

$$\begin{aligned} V_t(e_1, e_2, b_-, a_-) = \max_{c,b,a,\lambda,\varphi^b,\varphi^a} \ & \frac{c^{1-\gamma}}{1-\gamma} + \beta \sum_{e_1', e_2'} P(e_1', e_2' | e_1, e_2) V_{t+1}(e_1', e_2', b, a) \\ & + \lambda \{ w_t e \bar{l}_t + (1 - \xi)(1 + r_t^b) b_- + (1 + r_t^a) a_- \\ & - c - b - a - \eta_t \chi_t (a - (1 + r_t^a) a_-, a_-) \} + \varphi^b b + \varphi^a a. \end{aligned}$$

$$\lambda = c^{-\gamma}, \tag{C.2}$$

$$\lambda = \beta \sum_{e_1', e_2'} P(e_1', e_2' | e_1, e_2) V_{b,t+1}(e_1', e_2', b, a) + \varphi^b, \tag{C.3}$$

$$\lambda \{ 1 + \eta_t \chi_{1,t}(a - (1 + r_t^a) a_-, a_-) \} = \beta \sum_{e_1', e_2'} P(e_1', e_2' | e_1, e_2) V_{a,t+1}(e_1', e_2', b, a) + \varphi^a, \tag{C.4}$$

$$V_{b,t}(e_1, e_2, b_-, a_-) = (1 - \xi)(1 + r_t^b) \lambda, \tag{C.5}$$

$$\begin{aligned} V_{a,t}(e_1, e_2, b_-, a_-) = \lambda \{ & (1 + r_t^a) + (1 + r_t^a) \eta_t \chi_{1,t}(a - (1 + r_t^a) a_-, a_-) \\ & - \eta_t \chi_{2,t}(a - (1 + r_t^a) a_-, a_-) \}, \end{aligned} \tag{C.6}$$

$$c + b + a + \eta_t \chi_t (a - (1 + r_t^a) a_-, a_-) = w_t e \bar{l}_t + (1 - \xi)(1 + r_t^b) b_- + (1 + r_t^a) a_-, \tag{C.7}$$

$$\varphi^b \geq 0, \quad b \geq 0, \quad \varphi^b b = 0, \quad \text{and} \tag{C.8}$$

$$\varphi^a \geq 0, \quad a \geq 0, \quad \varphi^a a = 0. \tag{C.9}$$

C.2.1.2 Firms

Under deterministic paths of $\{z_t, g_t, \mu_t, \eta_t, \nu_t\}_{t=0}^{\infty}$, firms solve the following optimization problem.

$$\max_{\{K_t, F_t, L_t, Y_t, I_t, \Pi_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} Q_{o,t} \Pi_t$$

$$s.t.$$

$$\Pi_t = Y_t - w_t L_t - I_t - \Phi(K_t, K_{t-1}) + F_t - (1 + r_{t-1}) F_{t-1} + \chi_t^{agg}, \tag{C.10}$$

$$Y_t = z_t K_{t-1}^{\alpha} (X_t L_t)^{1-\alpha}, \tag{C.11}$$

$$\nu_t I_t = K_t - (1 - \delta) K_{t-1}, \tag{C.12}$$

$$\nu_t \Phi(K_t, K_{t-1}) = \frac{\phi}{2} \left(\frac{K_t}{K_{t-1}} - g^* \right)^2 K_{t-1},$$

$$Q_{0,t} = \begin{cases} 1 & \text{if} \quad t = 0, \\ \frac{1}{\prod_{s=1}^{t} (1 + r_s^a)} & \text{otherwise, and} \end{cases}$$

$$\lim_{j \to \infty} \frac{F_{t+j}}{\prod_{s=1}^{j} (1 + r_{t+s}^a)} \leq 0.$$

The optimality conditions of the problem can be obtained as follows.

$$\max_{\{K_t, F_t, L_t\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} Q_{0,t} \Bigg[z_t K_{t-1}^{\alpha} (X_t L_t)^{1-\alpha} - w_t L_t - \frac{1}{\nu_t} \big(K_t + (1 - \delta) K_{t-1} \big)$$
$$- \frac{1}{\nu_t} \frac{\phi}{2} \left(\frac{K_t}{K_{t-1}} - g^* \right)^2 K_{t-1} + F_t - (1 + r_{t-1}) F_{t-1} + \chi_t^{agg} \Bigg].$$

$$\begin{aligned} (1+r_{t+1}^a) \frac{1}{\nu_t} \left\{ 1 + \phi \left(\frac{K_t}{K_{t-1}} - g^* \right) \right\} &= \alpha z_{t+1} \left(\frac{K_t}{X_{t+1} L_{t+1}} \right)^{\alpha - 1} \\ &+ \frac{1}{\nu_{t+1}} \left\{ 1 - \delta + \phi \left(\frac{K_{t+1}}{K_t} - g^* \right) \frac{K_{t+1}}{K_t} - \frac{\phi}{2} \left(\frac{K_{t+1}}{K_t} - g^* \right)^2 \right\}, \quad t \geq 0, \end{aligned} \tag{C.13}$$

$$1 + r_{t+1}^a = 1 + r_t, \quad t \geq 0, \quad \text{and} \tag{C.14}$$

$$w_t = (1-\alpha) z_t X_t \left(\frac{K_{t-1}}{X_t L_t} \right)^{\alpha}. \tag{C.15}$$

C.2.1.3 Other Parts

The rest of the model (other than the households' problem in Appendix C.2.1.1 and the firms' problem in Appendix C.2.1.2) remains the same regardless of whether aggregate uncertainty is present or not. In other words, the law of motion for $\Psi_t(e_1, e_2, b_-, a_-)$ (equation (3.3)), aggregation of quantities (equation (3.4)) and households' budget constraints (equation (3.5)), the labor union's intratemporal labor supply decision (equation (3.6)), domestic banks' intratemporally equalized financing costs between the two sources (equation (3.7)), the relationship between illiquid asset returns and firms' profits and total values (equation (3.9)), the determination of the interest rates in the international financial market (equations (3.11) and (3.12)), the market clearing conditions (equations (3.14), (3.15), and (3.16)), the resource constraint (equation (3.17)), and the identity equation for the trade balance (equation (3.18)) hold true regardless of whether the economy faces aggregate uncertainty or it faces deterministic paths of $\{z_t, g_t, \mu_t, \eta_t, \nu_t\}_{t=0}^{\infty}$.

C.2.1.4 Equilibrium under Deterministic Paths of Aggregate Exogenous Variables

Given the initial conditions on $\Psi_0(e_1, e_2, b_-, a_-)$, X_{-1}, A_{-1}, K_{-1}, D_{-1}, B_{-1}, F_{-1}, r_{-1}, and deterministic paths of aggregate exogenous variables $\{z_t, g_t, \mu_t, \eta_t, \nu_t\}_{t=0}^{\infty}$,

i) individual households' policy functions $\{c_t(e_1, e_2, b_-, a_-), b_t(e_1, e_2, b_-, a_-), a_t(e_1, e_2, b_-, a_-)\}_{t=0}^{\infty}$, first-order derivatives of the value functions $\{V_{b,t}(e_1, e_2, b_-, a_-), V_{a,t}(e_1, e_2, b_-, a_-)\}_{t=0}^{\infty}$, and Lagrangian multipliers $\{\lambda_t(e_1, e_2, b_-, a_-), \varphi_t^b(e_1, e_2, b_-, a_-), \varphi_t^a(e_1, e_2, b_-, a_-)\}_{t=0}^{\infty}$ that satisfy households' optimality conditions (C.2), (C.3), (C.4), (C.5), (C.6), (C.7), (C.8), and (C.9),

ii) cross-sectional cumulative distributions $\{\Psi_t(e_1, e_2, b_-, a_-)\}_{t=1}^{\infty}$ that evolve over time according to equation (3.3),

iii) aggregate variables $\{C_t, B_t, A_t, \chi_t^{agg}\}_{t=0}^{\infty}$ constructed by aggregating corresponding individual variables according to equation (3.4),

iv) prices and aggregate variables $\{r_t^b, r_t^a, r_t, w_t, q_t, \bar{l}_t, L_t, \Pi_t, Y_t, I_t, K_t, F_t, D_t, \hat{D}_t, TB_t\}_{t=0}^{\infty}$ satisfying firms' optimality conditions (C.10), (C.11), (C.12), (C.13), (C.14), and (C.15), and other equilibrium conditions (3.6), (3.7), (3.9), (3.11), (3.12), (3.14), (3.15), (3.16), and (3.18)

constitute the equilibrium of the economy.

C.2.2 Detrended Equilibrium under Deterministic Paths of Aggregate Exogenous Variables

C.2.2.1 Detrending

Since the equilibrium characterized in subsection C.2.1 exhibits nonstationarity inherited from the stochastic trend $\{X_t\}_{t=0}^{\infty}$, we need to detrend the equilibrium to make it stationary. To this end, I detrend the variables and functions as follows.[9]

$$\tilde{c}_{i,t} := c_{i,t}/X_{t-1}, \quad \tilde{b}_{i,t} := b_{i,t}/X_t, \quad \tilde{a}_{i,t} := a_{i,t}/X_t,$$

$$\tilde{\lambda}_{i,t} := \lambda_{i,t}/X_{t-1}^{-\gamma}, \quad \tilde{\varphi}_{i,t}^b := \varphi_{i,t}^b/X_{t-1}^{-\gamma}, \quad \tilde{\varphi}_{i,t}^a := \varphi_{i,t}^a/X_{t-1}^{-\gamma},$$

$$\tilde{Y}_t := Y_t/X_{t-1}, \quad \tilde{C}_t := C_t/X_{t-1}, \quad \tilde{I}_t := I_t/X_{t-1},$$

$$\tilde{\chi}_t^{agg} := \chi_t^{agg}/X_{t-1}, \quad \tilde{w}_t := w_t/X_{t-1}, \quad \tilde{\Pi}_t := \Pi_t/X_{t-1}, \quad \tilde{TB}_t := TB_t/X_{t-1},$$

$$\tilde{B}_t := B_t/X_t, \quad \tilde{A}_t := A_t/X_t, \quad \tilde{q}_t := q_t/X_t,$$

$$\tilde{D}_t := D_t/X_t, \quad \tilde{\hat{D}}_t := \hat{D}_t/X_t, \quad \tilde{K}_t := K_t/X_t, \quad \text{and} \quad \tilde{F}_t := F_t/X_t.$$

[9] I detrend flow variables with X_{t-1} and stock variables with X_t as I find the consequent detrended equilibrium conditions convenient to deal with. However, how the variables are detrended is immaterial to the equilibrium dynamics of the original equilibrium once recovered from the equilibrium dynamics of the detrended equilibrium.

$$\tilde{\Psi}_t(e_1, e_2, \tilde{b}_-, \tilde{a}_-) := \Psi_t(e_1, e_2, \tilde{b}_- X_{t-1}, \tilde{a}_- X_{t-1}),$$

$$\tilde{V}_{b,t}(e_1, e_2, \tilde{b}_-, \tilde{a}_-) := V_{b,t}(e_1, e_2, \tilde{b}_- X_{t-1}, \tilde{a}_- X_{t-1})/X_{t-1}^{-\gamma},$$

$$\tilde{V}_{a,t}(e_1, e_2, \tilde{b}_-, \tilde{a}_-) := V_{a,t}(e_1, e_2, \tilde{b}_- X_{t-1}, \tilde{a}_- X_{t-1})/X_{t-1}^{-\gamma},$$

$$\tilde{c}_t(e_1, e_2, \tilde{b}_-, \tilde{a}_-) = c_t(e_1, e_2, \tilde{b}_- X_{t-1}, \tilde{a}_- X_{t-1})/X_{t-1},$$

$$\tilde{b}_t(e_1, e_2, \tilde{b}_-, \tilde{a}_-) = b_t(e_1, e_2, \tilde{b}_- X_{t-1}, \tilde{a}_- X_{t-1})/X_t,$$

$$\tilde{a}_t(e_1, e_2, \tilde{b}_-, \tilde{a}_-) = a_t(e_1, e_2, \tilde{b}_- X_{t-1}, \tilde{a}_- X_{t-1})/X_t,$$

$$\tilde{\lambda}_t(e_1, e_2, \tilde{b}_-, \tilde{a}_-) = \lambda_t(e_1, e_2, \tilde{b}_- X_{t-1}, \tilde{a}_- X_{t-1})/X_{t-1}^{-\gamma},$$

$$\tilde{\varphi}_t^b(e_1, e_2, \tilde{b}_-, \tilde{a}_-) = \varphi_t^b(e_1, e_2, \tilde{b}_- X_{t-1}, \tilde{a}_- X_{t-1})/X_{t-1}^{-\gamma},$$

$$\tilde{\varphi}_t^a(e_1, e_2, \tilde{b}_-, \tilde{a}_-) = \varphi_t^a(e_1, e_2, \tilde{b}_- X_{t-1}, \tilde{a}_- X_{t-1})/X_{t-1}^{-\gamma}, \quad \text{and}$$

$$\tilde{\chi}_t(\tilde{v}, \tilde{a}_-) := \chi_1 \left| \frac{\tilde{v}}{(1 + r_t^a)\tilde{a}_- + \chi_0} \right|^{\chi_2} \big((1 + r_t^a)\tilde{a}_- + \chi_0\big).$$

The first-order derivatives of $\tilde{\chi}_t(\tilde{v}, \tilde{a}_-)$ are

$$\tilde{\chi}_{1,t}(\tilde{v}, \tilde{a}_-) = sign(\tilde{v})\chi_1\chi_2 \left| \frac{\tilde{v}}{(1 + r_t^a)\tilde{a}_- + \chi_0} \right|^{\chi_2 - 1}, \quad \text{and}$$

$$\tilde{\chi}_{2,t}(\tilde{v}, \tilde{a}_-) = \chi_1(1 - \chi_2) \left| \frac{\tilde{v}}{(1 + r_t^a)\tilde{a}_- + \chi_0} \right|^{\chi_2} (1 + r_t^a).$$

Note that when $v_{i,t} = a_{i,t} - (1 + r_t^a)a_{i,t-1}$ and $\tilde{v}_{i,t} = v_{i,t}/X_{t-1} = g_t\tilde{a}_{i,t} - (1 + r_t^a)\tilde{a}_{i,t-1}$, the following relationships hold.

$$\tilde{\chi}_t(\tilde{v}_{i,t}, \tilde{a}_{i,t-1}) = \chi_t(v_{i,t}, a_{i,t-1})/X_{t-1},$$

$$\tilde{\chi}_{1,t}(\tilde{v}_{i,t}, \tilde{a}_{i,t-1}) = \chi_{1,t}(v_{i,t}, a_{i,t-1}), \quad \text{and}$$

$$\tilde{\chi}_{2,t}(\tilde{v}_{i,t}, \tilde{a}_{i,t-1}) = \chi_{2,t}(v_{i,t}, a_{i,t-1}).$$

The optimality conditions of households are detrended as follows.

$$\tilde{\lambda} = \tilde{c}^{-\gamma}, \tag{C.16}$$

$$\tilde{\lambda} = \beta g_t^{-\gamma} \sum_{e_1', e_2'} P(e_1', e_2' | e_1, e_2) \tilde{V}_{b,t+1}(e_1', e_2', \tilde{b}, \tilde{a}) + \tilde{\varphi}^b, \tag{C.17}$$

$$\begin{aligned} &\tilde{\lambda}\{1+\eta_t \tilde{\chi}_{1,t}(g_t \tilde{a} - (1+r_t^a)\tilde{a}_-, \tilde{a}_-)\} \\ &\qquad = \beta g_t^{-\gamma} \sum_{e_1', e_2'} P(e_1', e_2' | e_1, e_2) \tilde{V}_{a,t+1}(e_1', e_2', \tilde{b}, \tilde{a}) + \tilde{\varphi}^a, \end{aligned} \tag{C.18}$$

$$\tilde{V}_{b,t}(e_1, e_2, \tilde{b}_-, \tilde{a}_-) = (1-\xi)(1+r_t^b)\tilde{\lambda}, \tag{C.19}$$

$$\begin{aligned} \tilde{V}_{a,t}(e_1, e_2, \tilde{b}_-, \tilde{a}_-) = \tilde{\lambda}\{&(1+r_t^a) + (1+r_t^a)\eta_t \tilde{\chi}_{1,t}(g_t \tilde{a} - (1+r_t^a)\tilde{a}_-, \tilde{a}_-) \\ &- \eta_t \tilde{\chi}_{2,t}(g_t \tilde{a} - (1+r_t^a)\tilde{a}_-, \tilde{a}_-)\}, \end{aligned} \tag{C.20}$$

$$\tilde{c} + g_t \tilde{b} + g_t \tilde{a} + \eta_t \tilde{\chi}_t(g_t \tilde{a} - (1+r_t^a)\tilde{a}_-, \tilde{a}_-) = \tilde{w}_t e \bar{l}_t + (1-\xi)(1+r_t^b)\tilde{b}_- + (1+r_t^a)\tilde{a}_-, \tag{C.21}$$

$$\tilde{\varphi}^b \geq 0, \quad \tilde{b} \geq 0, \quad \tilde{\varphi}^b \tilde{b} = 0, \quad \text{and} \tag{C.22}$$

$$\tilde{\varphi}^a \geq 0, \quad \tilde{a} \geq 0, \quad \tilde{\varphi}^a \tilde{a} = 0. \tag{C.23}$$

The optimality conditions of firms are detrended as follows.

$$\tilde{\Pi}_t = \tilde{Y}_t - \tilde{w}_t L_t - \tilde{I}_t - \frac{1}{\nu_t}\frac{\phi}{2}\left(\frac{\tilde{K}_t}{\tilde{K}_{t-1}} g_t - g^*\right)^2 \tilde{K}_{t-1} + g_t \tilde{F}_t - (1+r_{t-1})\tilde{F}_{t-1} + \tilde{\chi}_t^{agg}, \tag{C.24}$$

$$\tilde{Y}_t = z_t g_t^{1-\alpha} \tilde{K}_{t-1}^{\alpha} L_t^{1-\alpha}, \tag{C.25}$$

$$\tilde{I}_t = \frac{1}{\nu_t}\left(g_t \tilde{K}_t - (1-\delta)\tilde{K}_{t-1}\right), \tag{C.26}$$

$$\begin{aligned} &(1+r_t)\frac{1}{\nu_t}\left\{1 + \phi\left(\frac{\tilde{K}_t}{\tilde{K}_{t-1}} g_t - g^*\right)\right\} = \alpha z_{t+1} g_{t+1}^{1-\alpha}\left(\frac{\tilde{K}_t}{L_{t+1}}\right)^{\alpha-1} \\ &+ \frac{1}{\nu_{t+1}}\left\{1 - \delta + \phi\left(\frac{\tilde{K}_{t+1}}{\tilde{K}_t} g_{t+1} - g^*\right)\frac{\tilde{K}_{t+1}}{\tilde{K}_t} g_{t+1} - \frac{\phi}{2}\left(\frac{\tilde{K}_{t+1}}{\tilde{K}_t} g_{t+1} - g^*\right)^2\right\}, \quad t \geq 0, \end{aligned} \tag{C.27}$$

$$1 + r^a_{t+1} = 1 + r_t, \quad t \geq 0, \quad \text{and} \tag{C.28}$$

$$\tilde{w}_t = (1-\alpha) z_t g_t^{1-\alpha} \left(\frac{\tilde{K}_{t-1}}{L_t} \right)^{\alpha}. \tag{C.29}$$

The other equilibrium conditions (3.3), (3.4), (3.6), (3.7), (3.9), (3.11),(3.12), (3.14), (3.15), (3.16), and (3.18) are detrended as follows.

$$\begin{aligned} \tilde{\Psi}_{t+1}(e'_1, e'_2, \tilde{b}, \tilde{a}) = \int_{e_1, e_2, \tilde{b}_-, \tilde{a}_-} & P(e_{1,t+1} \leq e'_1 | e_{1,t} = e_1) P(e_{2,t+1} \leq e'_2) \\ & I_{\{\tilde{b}_t(e_1,e_2,\tilde{b}_-,\tilde{a}_-) \leq \tilde{b},\ \tilde{a}_t(e_1,e_2,\tilde{b}_-,\tilde{a}_-) \leq \tilde{a}\}}(e_1, e_2, \tilde{b}_-, \tilde{a}_-)\, d\tilde{\Psi}_t, \end{aligned} \tag{C.30}$$

$$\begin{aligned} \tilde{C}_t &= \int_{e_1,e_2,\tilde{b}_-,\tilde{a}_-} \tilde{c}_t(e_1, e_2, \tilde{b}_-, \tilde{a}_-)\, d\tilde{\Psi}_t, \\ \tilde{B}_t &= \int_{e_1,e_2,\tilde{b}_-,\tilde{a}_-} \tilde{b}_t(e_1, e_2, \tilde{b}_-, \tilde{a}_-)\, d\tilde{\Psi}_t, \\ \tilde{A}_t &= \int_{e_1,e_2,\tilde{b}_-,\tilde{a}_-} \tilde{a}_t(e_1, e_2, \tilde{b}_-, \tilde{a}_-)\, d\tilde{\Psi}_t, \quad \text{and} \\ \tilde{\chi}^{agg}_t &= \int_{e_1,e_2,\tilde{b}_-,\tilde{a}_-} \eta_t \tilde{\chi}_t(g_t \tilde{a}_t(e_1, e_2, \tilde{b}_-, \tilde{a}_-) - (1 + r^a_t)\tilde{a}_-, \tilde{a}_-)\, d\tilde{\Psi}_t, \end{aligned} \tag{C.31}$$

$$\tilde{w}_t \bar{e}^{1+\omega} = \kappa L_t^{\omega}, \tag{C.32}$$

$$1 + r^b_t = 1 + r_{t-1}, \quad t \geq 0, \tag{C.33}$$

$$1 + r^a_t = \frac{\tilde{\Pi}_t + g_t \tilde{q}_t}{\tilde{q}_{t-1}}, \quad t \geq 0, \tag{C.34}$$

$$r_t = r^* + \psi \left\{ \exp\left(\frac{\tilde{D}_t - \tilde{D}^*}{\tilde{Y}^*} \right) - 1 \right\} - \theta_z (z_t - 1) - \theta_g \left(\frac{g_t}{g^*} - 1 \right) + \mu_t - 1, \tag{C.35}$$

$$\tilde{\tilde{D}}_t = \tilde{D}_t, \tag{C.36}$$

$$L_t = \bar{e} \bar{l}_t, \tag{C.37}$$

$$\tilde{F}_t - \tilde{D}_t = \tilde{B}_t, \tag{C.38}$$

$$\tilde{q}_t = \tilde{A}_t, \quad \text{and} \tag{C.39}$$

$$\tilde{TB}_t = -g_t \tilde{D}_t + (1 + r_{t-1})\tilde{D}_{t-1}. \tag{C.40}$$

In addition, the aggregated budget constraint of households (3.5) and the resource constraint (3.17) are detrended as follows.

$$\tilde{C}_t + g_t \tilde{B}_t + g_t \tilde{A}_t + \tilde{\chi}_t^{agg} = \tilde{w}_t \bar{e} \bar{l}_t + (1 - \xi)(1 + r_t^b)\tilde{B}_{t-1} + (1 + r_t^a)\tilde{A}_{t-1}, \quad \text{and} \tag{C.41}$$

$$\begin{aligned} \tilde{C}_t + \tilde{I}_t + \frac{1}{\nu_t}\frac{\phi}{2}\left(\frac{\tilde{K}_t}{\tilde{K}_{t-1}} g_t - g^*\right)^2 \tilde{K}_{t-1} + \xi(1 + r_{t-1})\tilde{B}_{t-1} \\ = \tilde{Y}_t + g_t \tilde{D}_t - (1 + r_{t-1})\tilde{D}_{t-1}. \end{aligned} \tag{C.42}$$

C.2.2.2 Detrended Equilibrium under Deterministic Paths of Aggregate Exogenous Variables

Given the initial conditions on $\tilde{\Psi}_0(e_1, e_2, \tilde{b}_-, \tilde{a}_-)$, $\tilde{A}_{-1}$, $\tilde{K}_{-1}$, $\tilde{D}_{-1}$, $\tilde{B}_{-1}$, $\tilde{F}_{-1}$, r_{-1}, and deterministic paths of aggregate exogenous variables $\{z_t, g_t, \mu_t, \eta_t, \nu_t\}_{t=0}^{\infty}$,

i) individual households' detrended policy functions $\{\tilde{c}_t(e_1, e_2, \tilde{b}_-, \tilde{a}_-), \tilde{b}_t(e_1, e_2, \tilde{b}_-, \tilde{a}_-),$ $\tilde{a}_t(e_1, e_2, \tilde{b}_-, \tilde{a}_-)\}_{t=0}^{\infty}$, detrended first-order derivatives of the value functions $\{\tilde{V}_{b,t}(e_1, e_2, \tilde{b}_-, \tilde{a}_-), \tilde{V}_{a,t}(e_1, e_2, \tilde{b}_-, \tilde{a}_-)\}_{t=0}^{\infty}$, and detrended Lagrangian multipliers $\{\tilde{\lambda}_t(e_1, e_2, \tilde{b}_-, \tilde{a}_-), \tilde{\varphi}_t^b(e_1, e_2, \tilde{b}_-, \tilde{a}_-), \tilde{\varphi}_t^a(e_1, e_2, \tilde{b}_-, \tilde{a}_-)\}_{t=0}^{\infty}$ that satisfy households' detrended optimality conditions (C.16), (C.17), (C.18), (C.19), (C.20), (C.21), (C.22), and (C.23),

ii) cross-sectional cumulative distributions $\{\tilde{\Psi}_t(e_1, e_2, \tilde{b}_-, \tilde{a}_-)\}_{t=1}^{\infty}$ that evolve over time according to equation (C.30),

iii) detrended aggregate variables $\{\tilde{C}_t, \tilde{B}_t, \tilde{A}_t, \tilde{\chi}_t^{agg}\}_{t=0}^{\infty}$ constructed by aggregating corresponding detrended individual variables according to equation (C.31),

iv) detrended prices and aggregate variables $\{r_t^b, r_t^a, r_t, \tilde{w}_t, \tilde{q}_t, \bar{l}_t, L_t, \tilde{\Pi}_t, \tilde{Y}_t, \tilde{I}_t, \tilde{K}_t, \tilde{F}_t, \tilde{D}_t, \tilde{TB}_t\}_{t=0}^{\infty}$ satisfying firms' optimality conditions (C.24), (C.25), (C.26), (C.27), (C.28), and (C.29), and other equilibrium conditions (C.32), (C.33), (C.34), (C.35), (C.37), (C.38), (C.39), and (C.40) constitute the detrended equilibrium of the economy.

C.2.2.3 Steady State of the Detrended Equilibrium

I solve the detrended equilibrium using Auclert et al. (2019)'s method, and the first step is to solve its steady state. This subsection specifies the equilibrium conditions in the steady state of the detrended equilibrium. For any variable U_t and any function $F_t(\cdot)$, U_{ss} and $F_{ss}(\cdot)$ represent their steady state values, respectively.

The steady state values of the exogenous variables $\{z_t, g_t, \mu_t, \eta_t, \nu_t\}_{t=0}^{\infty}$ are determined as follows.

$$z_{ss} = 1, \quad g_{ss} = g^*, \quad \mu_{ss} = 1, \quad \eta_{ss} = 1, \quad \text{and} \quad \nu_{ss} = 1$$

By the definition of $\tilde{D}^*$ and $\tilde{Y}^*$, we have

$$\tilde{D}_{ss} = \tilde{D}^* \quad \text{and} \quad \tilde{Y}_{ss} = \tilde{Y}^*.$$

In the steady state, households' detrended policy functions $\tilde{c}_{ss}(e_1, e_2, \tilde{b}_-, \tilde{a}_-)$, $\tilde{b}_{ss}(e_1, e_2, \tilde{b}_-, \tilde{a}_-)$, and $\tilde{a}_{ss}(e_1, e_2, \tilde{b}_-, \tilde{a}_-)$, detrended first-order derivatives of the value functions $\tilde{V}_{b,ss}(e_1, e_2, \tilde{b}_-, \tilde{a}_-)$ and $\tilde{V}_{a,ss}(e_1, e_2, \tilde{b}_-, \tilde{a}_-)$, and detrended Lagrangian multipliers $\tilde{\lambda}_{ss}(e_1, e_2, \tilde{b}_-, \tilde{a}_-)$, $\tilde{\varphi}^b_{ss}(e_1, e_2, \tilde{b}_-, \tilde{a}_-)$, and $\tilde{\varphi}^a_{ss}(e_1, e_2, \tilde{b}_-, \tilde{a}_-)$ solve the following optimality conditions (C.43), (C.44), (C.45), (C.46), (C.47), (C.48), (C.49), and (C.50).

$$\tilde{\lambda} = \tilde{c}^{-\gamma}, \tag{C.43}$$

$$\tilde{\lambda} = \beta g_{ss}^{-\gamma} \sum_{e_1', e_2'} P(e_1', e_2' | e_1, e_2) \tilde{V}_{b,ss}(e_1', e_2', \tilde{b}, \tilde{a}) + \tilde{\varphi}^b, \tag{C.44}$$

$$\begin{aligned} \tilde{\lambda}\{1 + &\tilde{\chi}_{1,ss}(g_{ss}\tilde{a} - (1 + r^a_{ss})\tilde{a}_-, \tilde{a}_-)\} \\ &= \beta g_{ss}^{-\gamma} \sum_{e_1', e_2'} P(e_1', e_2' | e_1, e_2) \tilde{V}_{a,ss}(e_1', e_2', \tilde{b}, \tilde{a}) + \tilde{\varphi}^a, \end{aligned} \tag{C.45}$$

$$\tilde{V}_{b,ss}(e_1, e_2, \tilde{b}_-, \tilde{a}_-) = (1-\xi)(1+r_{ss}^b)\tilde{\lambda}, \tag{C.46}$$

$$\begin{aligned}\tilde{V}_{a,ss}(e_1, e_2, \tilde{b}_-, \tilde{a}_-) = \tilde{\lambda}\{&(1+r_{ss}^a) + (1+r_{ss}^a)\tilde{\chi}_{1,ss}(g_{ss}\tilde{a} - (1+r_{ss}^a)\tilde{a}_-, \tilde{a}_-) \\ &- \tilde{\chi}_{2,ss}(g_{ss}\tilde{a} - (1+r_{ss}^a)\tilde{a}_-, \tilde{a}_-)\},\end{aligned} \tag{C.47}$$

$$\begin{aligned}\tilde{c} + g_{ss}\tilde{b} + g_{ss}\tilde{a} + &\tilde{\chi}_{ss}(g_{ss}\tilde{a} - (1+r_{ss}^a)\tilde{a}_-, \tilde{a}_-) \\ &= \tilde{w}_{ss}e\bar{l}_{ss} + (1-\xi)(1+r_{ss}^b)\tilde{b}_- + (1+r_{ss}^a)\tilde{a}_-,\end{aligned} \tag{C.48}$$

$$\tilde{\varphi}^b \geq 0, \quad \tilde{b} \geq 0, \quad \tilde{\varphi}^b\tilde{b} = 0, \quad \text{and} \tag{C.49}$$

$$\tilde{\varphi}^a \geq 0, \quad \tilde{a} \geq 0, \quad \tilde{\varphi}^a\tilde{a} = 0. \tag{C.50}$$

The detrended optimality conditions of firms become the following equations in the steady state.

$$\tilde{\Pi}_{ss} = \tilde{Y}_{ss} - \tilde{w}_{ss}L_{ss} - \tilde{I}_{ss} - (1 + r_{ss} - g_{ss})\tilde{F}_{ss} + \tilde{\chi}_{ss}^{agg}, \tag{C.51}$$

$$\tilde{Y}_{ss} = z_{ss}g_{ss}^{1-\alpha}\tilde{K}_{ss}^{\alpha}L_{ss}^{1-\alpha}, \tag{C.52}$$

$$\tilde{I}_{ss} = (g_{ss} - 1 + \delta)\tilde{K}_{ss}, \tag{C.53}$$

$$r_{ss} + \delta = \alpha z_{ss}g_{ss}^{1-\alpha}\left(\frac{\tilde{K}_{ss}}{L_{ss}}\right)^{\alpha-1} \quad \left(= \alpha\frac{\tilde{Y}_{ss}}{\tilde{K}_{ss}}\right), \tag{C.54}$$

$$r_{ss}^a = r_{ss}, \quad \text{and} \tag{C.55}$$

$$\tilde{w}_{ss} = (1-\alpha)z_{ss}g_{ss}^{1-\alpha}\left(\frac{\tilde{K}_{ss}}{L_{ss}}\right)^{\alpha} \quad \left(= (1-\alpha)\frac{\tilde{Y}_{ss}}{L_{ss}}\right). \tag{C.56}$$

The other detrended equilibrium conditions become the following equations in the steady state.

$$\begin{aligned}\tilde{\Psi}_{ss}(e_1', e_2', \tilde{b}, \tilde{a}) = \int_{e_1, e_2, \tilde{b}_-, \tilde{a}_-} &P(e_{1,t+1} \leq e_1' | e_{1,t} = e_1)P(e_{2,t+1} \leq e_2') \\ &I_{\{\tilde{b}_t(e_1,e_2,\tilde{b}_-,\tilde{a}_-)\leq\tilde{b},\ \tilde{a}_t(e_1,e_2,\tilde{b}_-,\tilde{a}_-)\leq\tilde{a}\}}(e_1, e_2, \tilde{b}_-, \tilde{a}_-)\, d\tilde{\Psi}_{ss},\end{aligned} \tag{C.57}$$

$$
\begin{aligned}
\tilde{C}_{ss} &= \int_{e_1,e_2,\tilde{b}_-,\tilde{a}_-} \tilde{c}_{ss}(e_1, e_2, \tilde{b}_-, \tilde{a}_-)\, d\tilde{\Psi}_{ss}, \\
\tilde{B}_{ss} &= \int_{e_1,e_2,\tilde{b}_-,\tilde{a}_-} \tilde{b}_{ss}(e_1, e_2, \tilde{b}_-, \tilde{a}_-)\, d\tilde{\Psi}_{ss}, \\
\tilde{A}_{ss} &= \int_{e_1,e_2,\tilde{b}_-,\tilde{a}_-} \tilde{a}_{ss}(e_1, e_2, \tilde{b}_-, \tilde{a}_-)\, d\tilde{\Psi}_{ss}, \quad \text{and} \\
\tilde{\chi}^{agg}_{ss} &= \int_{e_1,e_2,\tilde{b}_-,\tilde{a}_-} \tilde{\chi}_{ss}(g_{ss}\tilde{a}_{ss}(e_1, e_2, \tilde{b}_-, \tilde{a}_-) - (1 + r^a_{ss})\tilde{a}_-, \tilde{a}_-)\, d\tilde{\Psi}_{ss},
\end{aligned}
\tag{C.58}
$$

$$\tilde{w}_{ss}\bar{e}^{1+\omega} = \kappa L^{\omega}_{ss}, \tag{C.59}$$

$$r^b_{ss} = r_{ss}, \tag{C.60}$$

$$\Pi_{ss} = (1 + r^a_{ss} - g_{ss})q_{ss}, \tag{C.61}$$

$$r_{ss} = r^*, \tag{C.62}$$

$$L_{ss} = \bar{e}\bar{l}_{ss}, \tag{C.63}$$

$$\tilde{F}_{ss} - \tilde{D}_{ss} = \tilde{B}_{ss}, \tag{C.64}$$

$$\tilde{q}_{ss} = \tilde{A}_{ss}, \quad \text{and} \tag{C.65}$$

$$\tilde{TB}_{ss} = (1 + r_{ss} - g_{ss})\tilde{D}_{ss}. \tag{C.66}$$

In addition, the detrended aggregated budget constraint of households (C.41) and the detrended resource constraint (C.42) become the following equations in the steady state.

$$\tilde{C}_{ss} + g_{ss}\tilde{B}_{ss} + g_{ss}\tilde{A}_{ss} + \tilde{\chi}^{agg}_{ss} = \tilde{w}_{ss}\bar{e}\bar{l}_t + (1 - \xi)(1 + r^b_{ss})\tilde{B}_{ss} + (1 + r^a_{ss})\tilde{A}_{ss}, \quad \text{and} \tag{C.67}$$

$$\tilde{C}_{ss} + \tilde{I}_{ss} + \xi(1 + r_{ss})\tilde{B}_{ss} = \tilde{Y}_{ss} - (1 + r_{ss} - g_{ss})\tilde{D}_{ss}. \tag{C.68}$$

By combining equations (C.61), (C.65), (C.51), (C.55), (C.56), (C.53), (C.54), and (C.64), we can obtain the following relationship among stock variables in the steady state.

$$\tilde{K}_{ss} + \frac{1}{1 + r_{ss} - g_{ss}} \tilde{\chi}^{agg}_{ss} = \tilde{A}_{ss} + \tilde{B}_{ss} + \tilde{D}_{ss} \tag{C.69}$$

C.2.3 Solving the Detrended Equilibrium using Auclert et al. (2019)'s Method

I solve the detrended equilibrium using Auclert et al. (2019)'s method. In this subsection, I briefly describe how this method solves the equilibrium. The first step is to solve heterogeneous households' policy functions and the stationary distribution over the household heterogeneity in the steady state. For this step, Auclert et al. (2019) develop a fast algorithm that extends Carroll (2006)'s method of endogenous gridpoints to the two-asset environment in order to solve the steady state of their two-asset HANK model. Since the household block of my model is almost identical to the household block of their model, I closely follow this algorithm to compute the steady state of my model. See Appendix B.1 of Auclert et al. (2019) for the details of this algorithm.[10]

Once the steady state is pinned down, Auclert et al. (2019)'s method computes the Jacobians of 'blocks'. Here, a 'block' is a function that maps the sequences of input variables $\{x_{1,t}, \cdots, x_{n_x,t}\}_{t=0}^T$ into the sequences of output variables $\{y_{1,t}, \cdots, y_{n_y,t}\}_{t=0}^T$ using a subset of equilibrium conditions. The Jacobian of the block is a matrix composed of the following elements. $\{\frac{\partial y_{j,s}}{\partial x_{i,t}}\}_{1\le i\le n_x,\ 1\le j\le n_y,\ 0\le s,t\le T}$. For example, the household block of my model maps the sequences of its input variables $\{\tilde{w}_t, r^a_t, r^b_t, g_t, \bar{l}_t, \eta_t\}_{t=0}^T$ into the sequences of its output variables $\{\tilde{C}_t, \tilde{B}_t, \tilde{A}_t\}_{t=0}^T$ using equilibrium conditions (C.16), (C.17), (C.18), (C.19), (C.20), (C.21), (C.22), and (C.23). The Jacobian of the household block is composed of $\left\{\frac{\partial y_s}{\partial x_t}\right\}_{x\in\{\tilde{w},r^a,r^b,g,\bar{l},\eta\},\ y\in\{\tilde{C},\tilde{B},\tilde{A}\},\ 0\le s,t\le T}$.

Figure C.1 is the directed acyclical graph (DAG) representation of the detrended equilibrium, in which blocks, input variables, and output variables are indicated. Each of the blue rectangles and red ellipses in the figure represent the blocks of the equilibrium. For each block, variables coming into the block and variables coming out of the block (indicated by arrows connecting blocks) are inputs and outputs of the block, respectively. Within each block, the bullet points and following

[10]For grids, I use 9 gridpoints for e_1, 13 gridpoints for e_2, and 70 gridpoints for each of $\tilde{b}_-$ and $\tilde{a}_-$.

parentheses indicate the names of the equilibrium conditions, corresponding equation numbers, and output variables pinned down by the equilibrium conditions.

Following the notations of Auclert et al. (2019), let Z be a stacked vector of the sequences of exogenous variables and U be a stacked vector of the sequences of unknown variables indicated in the black diamond box in Figure C.1. Moreover, let $H(U, Z)$ be a function that maps U and Z into a stacked vector of $\{H_{1,t}, H_{2,t}, H_{3,t}\}_{t=0}^{T}$ in which $H_{1,t}$,$H_{2,t}$, and $H_{3,t}$ are defined as

$$H_{1,t} = \tilde{A}_t - \tilde{q}_t, \quad H_{2,t} = \tilde{B}_t + \tilde{D}_t - \tilde{F}_t, \quad \text{and} \quad H_{3,t} = \tilde{\chi}_t^{agg} - \tilde{\chi}_{unknown,t}^{agg},$$

as indicated in the red ellipses of Figure C.1.

Under this formulation, 'solving the model' boils down to finding U that satisfies

$$H(U, Z) = 0$$

for given Z. Under the first-order approximation, this equation becomes

$$H_U dU + H_Z dZ = 0$$

$$\Leftrightarrow dU = -H_U^{-1} H_Z dZ. \tag{C.70}$$

By combining the Jacobians of the blocks through the Chain Rule, Auclert et al. (2019)'s method computes H_U and H_Z. Then, the method solves dU using equation (C.70), and recovers the linearized dynamics of other variables by again combining the Jacobians through the Chain Rule along the directed acyclical graph in Figure C.1.

In the whole computation procedure, the most time-consuming steps are i) solving the steady state and ii) computing the Jacobian of the household block. In particular, calibrating β, χ_1, and χ_2 requires solving the steady state multiple times, and this step takes longer than a day. However, once these parameters are calibrated and I have both the computed steady state and the Jacobian of the household block in my hand, the rest of the computation steps are very quick (taking less than

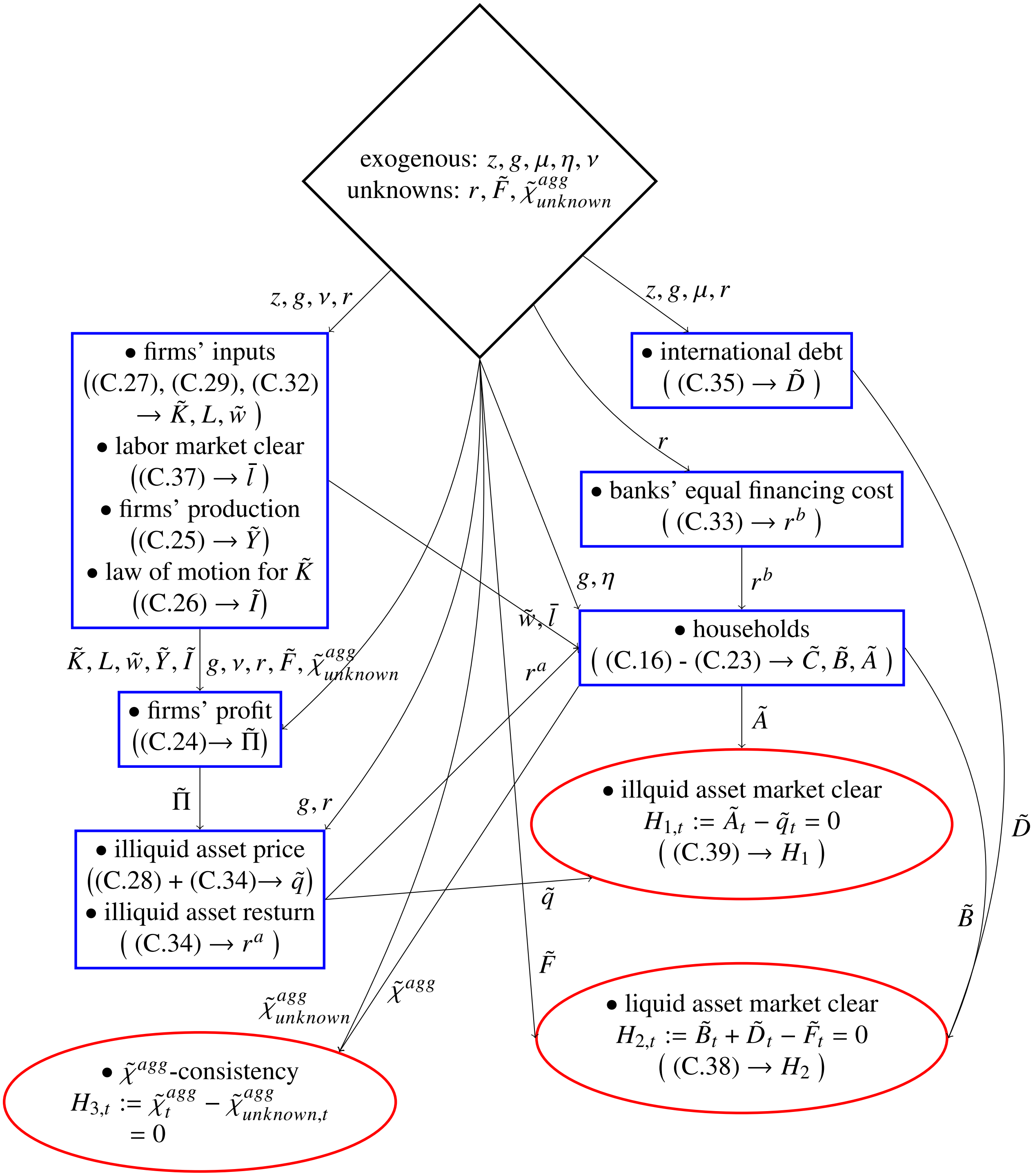


Figure C.1: Directed Acyclical Graph (DAG) representation of the detrended equilibrium a second). This is why the Bayesian estimation of the model is possible as long as the parameters to be estimated are not inside the household block.

C.2.4 Recovering the Original Equilibrium

Once the detrended equilibrium is solved, we can recover the original equilibrium. In particular, the figures and tables in this paper report results based on the following statistics of the original equilibrium: i) the standard deviations and correlations of $\Delta \log Y_t$, $\Delta \log C_t$, $\Delta \log I_t$, and $\Delta(TB_t/Y_t)$, and ii) the impulse responses of the model variables in terms of their deviations from the balanced growth path.

C.2.4.1 $\Delta \log Y_t$, $\Delta \log C_t$, $\Delta \log I_t$, and $\Delta(TB_t/Y_t)$ of the original equilibrium

$\Delta \log Y_t$, $\Delta \log C_t$, $\Delta \log I_t$, and $\Delta(TB_t/Y_t)$ of the original equilibrium are recovered using the following equations.

$$\Delta \log Y_t = \Delta \log \tilde{Y}_t - \Delta \log \tilde{Y}_{t-1} + \log g_{t-1},$$

$$\Delta \log C_t = \Delta \log \tilde{C}_t - \Delta \log \tilde{C}_{t-1} + \log g_{t-1},$$

$$\Delta \log I_t = \Delta \log \tilde{I}_t - \Delta \log \tilde{I}_{t-1} + \log g_{t-1}, \quad \text{and}$$

$$\Delta(TB_t/Y_t) = \frac{\tilde{TB}_t}{\tilde{Y}_t} - \frac{\tilde{TB}_{t-1}}{\tilde{Y}_{t-1}}.$$

C.2.4.2 Impulse Responses in terms of Deviations from the Balanced Growth Path

The impulse responses of the model variables in terms of their deviations from the balanced growth path in the original equilibrium are recovered as follows. First, I define the 'constant-growth trend of the balanced growth path' X_t^* as follows. Given that a shock is realized in period 0,

$$X_t^* = (g^*)^{t+1} X_{-1}.$$

Let M_t^f be one of the flow variables in the original equilibrium, which is detrended with X_{t-1}

in constructing the detrended equilibrium. (Variables Y_t, C_t, I_t, Π_t, and w_t belong to this category.) Let $\tilde{M}_t^f := M_t^f / X_{t-1}$ be the detrended variable, and $\tilde{M}_{ss}^f$ be the steady state value of $\tilde{M}_t^f$ in the detrended equilibrium. $\{M_t^f\}_{t=0}^{\infty}$ on the balanced growth path, which I denote as $\{M_t^{f*}\}_{t=0}^{\infty}$, is determined by

$$M_t^{f*} = \tilde{M}_{ss}^f X_{t-1}^*, \quad t \geq 0.$$

This is the path of $\{M_t^f\}_{t=0}^{\infty}$ when there is no shock in period 0. The impulse response of M_t^f in terms of their ratio deviations from the balanced growth path is constructed by

$$IRF_{M^f}(t) = \frac{M_t^f - M_t^{f*}}{M_t^{f*}} = \frac{M_t^f / X_{t-1}^* - \tilde{M}_{ss}^f}{\tilde{M}_{ss}^f}.$$

I compute this impulse response as follows. By solving the detrended equilibrium using Auclert et al. (2019)'s method, I obtain $d\tilde{M}_t^f = \tilde{M}_t^f - \tilde{M}_{ss}^f$, in which the d-operator on the left hand side means the level deviation from the steady state of the detrended equilibrium. Then, I use the following equation, which holds under the first-order approximation, to obtain $d(M_t^f / X_{t-1}^*) = M_t^f / X_{t-1}^* - \tilde{M}_{ss}^f$.

$$\begin{aligned}
d(M_t^f / X_{t-1}^*) &= d(\tilde{M}_t^f (X_{t-1}/X_{t-1}^*)) \\
&= d\tilde{M}_t^f + \tilde{M}_{ss}^f \, d(X_{t-1}/X_{t-1}^*) \\
&= d\tilde{M}_t^f + \tilde{M}_{ss}^f \, d\left(\frac{g_0}{g^*}\frac{g_1}{g^*} \cdots \frac{g_{t-1}}{g^*}\right) \\
&= d\tilde{M}_t^f + \frac{\tilde{M}_{ss}^f}{g^*}\left(\sum_{j=0}^{t-1} dg_j\right).
\end{aligned}$$

By dividing $d(M_t^f / X_{t-1}^*)$ with $\tilde{M}_{ss}^f$, I obtain $IRF_{M^f}(t)$.

Impulse responses for the stock variables can be computed in a similar way. Let M_t^s be one of the stock variables in the original equilibrium, which is detrended with X_t in the detrended equilibrium. (Variables K_t, A_t, B_t, D_t, and F_t belong to this category.) Let $\tilde{M}_t^s := M_t^s / X_t$ be the detrended variable, and $\tilde{M}_{ss}^s$ be the steady state value of $\tilde{M}_t^s$ in the detrended equilibrium. $\{M_t^s\}_{t=0}^{\infty}$

on the balanced growth path, which I denote as $\{M_t^{s*}\}_{t=0}^{\infty}$, is determined by

$$M_t^{s*} = \tilde{M}_{ss}^s X_t^*, \quad t \geq 0.$$

The impulse response of M_t^s in terms of their ratio deviations from the balanced growth path is constructed by

$$IRF_{M^s}(t) = \frac{M_t^s - M_t^{s*}}{M_t^{s*}} = \frac{M_t^s / X_t^* - \tilde{M}_{ss}^s}{\tilde{M}_{ss}^s}.$$

After obtaining $d\tilde{M}_t^s = \tilde{M}_t^s - \tilde{M}_{ss}^s$ by solving the detrended equilibrium with Auclert et al. (2019)'s method, I compute $d(M_t^s/X_t^*) = M_t^s/X_t^* - \tilde{M}_{ss}^s$ using the following first-order-approximated equation.

$$d(M_t^s/X_t^*) = d\tilde{M}_t^s + \frac{\tilde{M}_{ss}^s}{g^*}\left(\sum_{j=0}^{t} dg_j\right).$$

By dividing $d(M_t^s/X_t^*)$ with $\tilde{M}_{ss}^s$, I obtain $IRF_{M^s}(t)$.

There are variables in the original equilibrium that are not detrended in the detrended equilibrium. (Variables r_t^a, r_t^b, r_t, and L_t belong to this category). Let M_t^n be one of such variables. By construction, these variables have the same steady state values between the original equilibrium and the detrended equilibrium. For their impulse responses, I use their level deviations from their steady state values, $dM_t^n = M_t^n - M_{ss}^n$.[11]

C.3 Cross-autocorrelogram

This section compares the cross-autocorrelograms between the model (the baseline economy) and the data.

[11] In all the impulse response plots reported in this paper, I indicate in the label of the y-axis whether the ratio deviations are plotted or the level deviations are plotted.

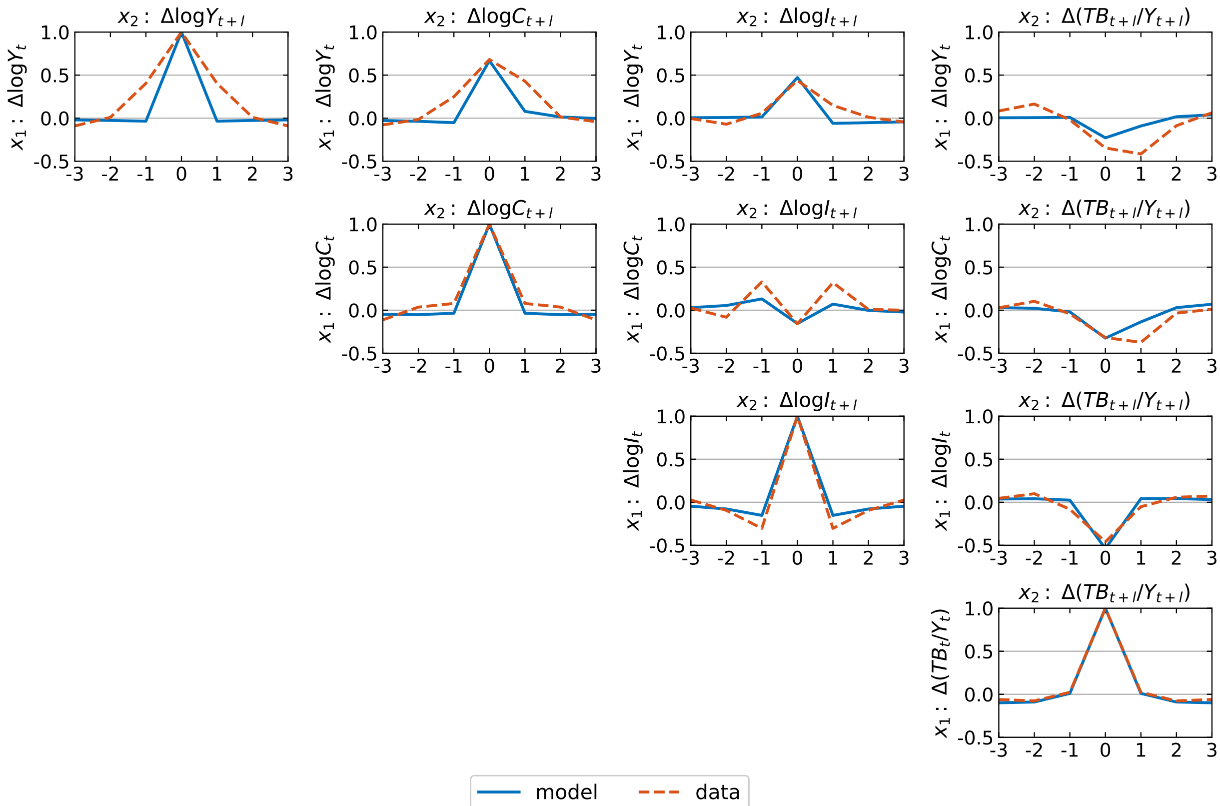


Figure C.2: cross-autocorrelogram $corr[x_{1,t}, x_{2,t+l}]$: model vs data

Notes: This figure plots the cross-autocorrelograms computed from the Peruvian macro data and those generated from the model after the calibration and Bayesian estimation discussed in section 3.4. The model statistics are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure.

C.4 Broader Recalibration for the Counterfactual Economy

I only recalibrate χ_1, χ_2, and β in the counterfactual experiment of the main text in section 3.5. Although χ_1, χ_2, and β are key determinants of the MPCs in the model, there are other parameters that also affect MPCs. Such parameters include the difference in return rates between liquid and illiquid assets ξ, and the parameters governing the labor productivity process ρ_{e_1}, σ_{e_1}, and σ_{e_2}. In this section, I run an alternative counterfactual experiment in which these parameters are also recalibrated. Specifically, I recalibrate ξ, ρ_{e_1}, σ_{e_1}, and σ_{e_2} using relevant U.S. data first and then recalibrate χ_1, χ_2, and β by targeting the U.S. MPC estimates and the Peruvian trade-balance-to-output ratio. Table C.2 reports the recalibrated values of the parameters.

Table C.2: Broader Recalibration for the Counterfactual Economy

	Description	Value	Target / source
labor income process			
ρ_{e_1}	persistence of the AR(1) component	0.988	PSID
σ_{e_1}	S.D. of shocks to the AR(1) component	0.073	PSID
σ_{e_2}	S.D. of shocks to the $i.i.d.$ component	0.605	PSID
long-run averages			
ξ	long-run average spread	0.006	FRB, OECD, U.S. CPI
targeting MPCs over the labor income deciles & Aggregate Wealth			
β	discount factor	0.970	MPC estimates (from PSID) and Peruvian TB/Y
χ_1	scale parameter of illiquid adj. cost	0.204	MPC estimates (from PSID) and Peruvian TB/Y
χ_2	convexity parameter of illiquid adj. cost	1.365	MPC estimates (from PSID) and Peruvian TB/Y

Parameters ρ_{e_1}, σ_{e_1}, and σ_{e_2} are recalibrated using the PSID data. Note that these parameters specify the quarterly labor productivity process in the model, while the PSID provides annual data. Given the frequency mismatch between the model and the data, I estimate these parameters according to the following steps. First, I estimate the annual income process from the PSID sample using Floden and Lindé (2001)'s method. Then, I find parameters ρ_{e_1}, σ_{e_1}, and σ_{e_2} for the quarterly labor productivity process that yield the same estimation result when I simulate annual income series by aggregating the model-generated quarterly income series over every four quarters and apply to the simulated annual series the same estimation procedure applied to the PSID data.

Parameter ξ is recalibrated to match the gap between U.S. real lending rates and deposit rates. The real lending rates and deposit rates are constructed by subtracting the expected inflation of the U.S. CPIs from the nominal lending rates and deposit rates, respectively. For the nominal lending rates, bank prime loan rates from Board of Governors of the Federal Reserve System (retrieved from FRED, Federal Reserve Bank of St. Louis) are used. For the nominal deposit rates, 3-month rates on Certificates of Deposit from OECD (retrieved from FRED, Federal Reserve Bank of St. Louis) are used.[12]

Once parameters ρ_{e_1}, σ_{e_1}, σ_{e_2}, and ξ are recalibrated, I recalibrate parameters χ_1, χ_2, and β by

[12] Although these two data series come from different sources, the real lending rates and real deposit rates constructed from each data series track each other very closely once the gross rates of the former are scaled by $(1-\xi)$.

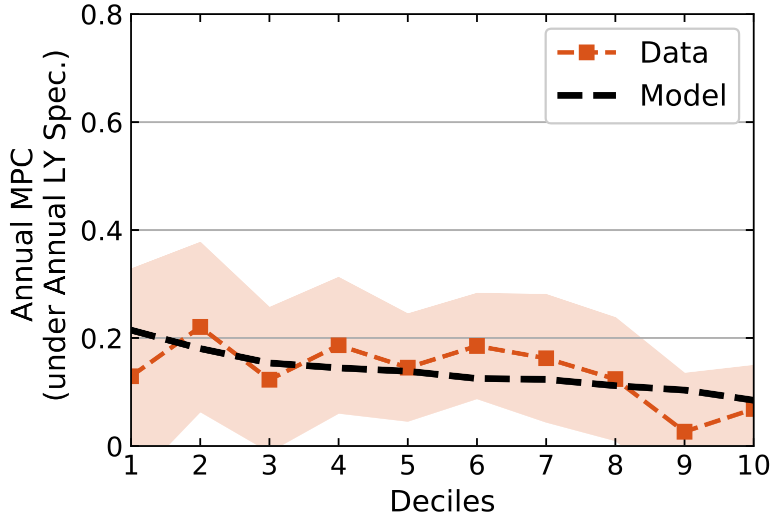


Figure C.3: Annual MPCs in U.S.: Data vs Model
under Broader Recalibration

Notes: Figure C.3 plots the annual MPC estimates from the PSID and their model counterparts under the broader recalibration in Appendix C.4. In computing the model counterparts of the estimates, I simulate annual consumption and income series by aggregating model-generated quarterly consumption and income series over every four quarters and then apply to the simulated annual data the same MPC estimation procedure applied to the PSID data.

targeting the U.S. MPC estimates of the labor income deciles and the Peruvian trade-balance-to-output ratio. Again, the calibration is successful despite the fact that I only use three parameters to target eleven moments. The model-generated trade-balance-to-output ratio on the balanced growth path is 0.042, and its data counterpart is 0.043. Moreover, Figure C.3 shows that the model-generated U.S. MPCs of the labor income deciles closely track the data counterparts.

Figure C.4 shows that under the broader recalibration of the counterfactual economy, the following patterns robustly appear: i) the MPC gap between Peru and the U.S. predicted by the model is narrower than that predicted by the model-free frequency conversion in Figure 3.1, and ii) despite this tendency, the model still predicts a substantial MPC gap between Peru and the U.S. In fact, the MPC gap under the broader recalibration in Figure C.4 is slightly larger than the gap under the benchmark recalibration in Figure 3.4.

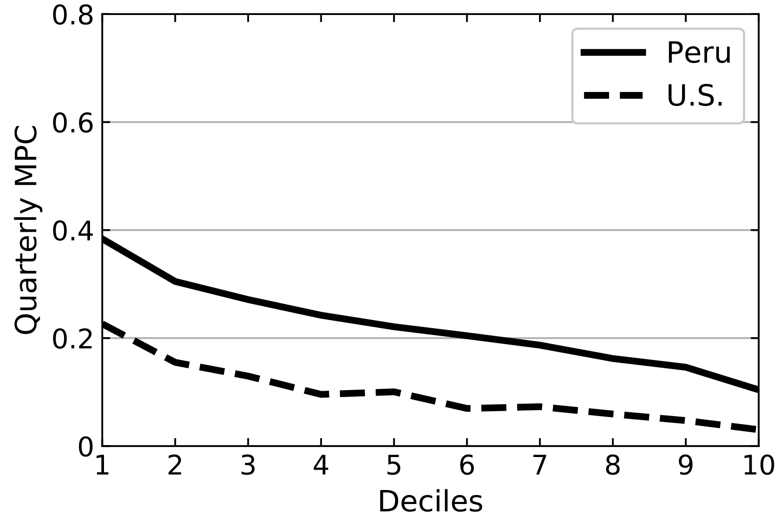


Figure C.4: Model-Predicted Quarterly MPCs: Peru and U.S.
under Broader Recalibration

Notes: Figure C.4 compares the model-predicted quarterly MPCs between the baseline economy and the counterfactual economy under the broader recalibration in Appendix C.4.

Table C.3 compares the standard deviations of output growth, consumption growth, and the ratio of the two between the baseline economy and the counterfactual economy under the broader recalibration. As we can see from this table, the phenomenon of excess consumption volatility robustly disappears in this alternative counterfactual experiment.

In the rest of this section, I also report the results of variance change decomposition and consumption response decomposition in this alternative counterfactual experiment under the broader

Table C.3: Absence of Excess Consumption Volatility in the Counterfactual Economy
under Broader Recalibration

	$\sigma(\Delta \log Y_t)$	$\sigma(\Delta \log C_t^{msd})$	$\frac{\sigma(\Delta \log C_t^{msd})}{\sigma(\Delta \log Y_t)}$
Baseline	0.029	0.037	1.283
	(0.002)	(0.002)	(0.075)
Counterfactual	0.028	0.026	0.914
	(0.002)	(0.002)	(0.071)

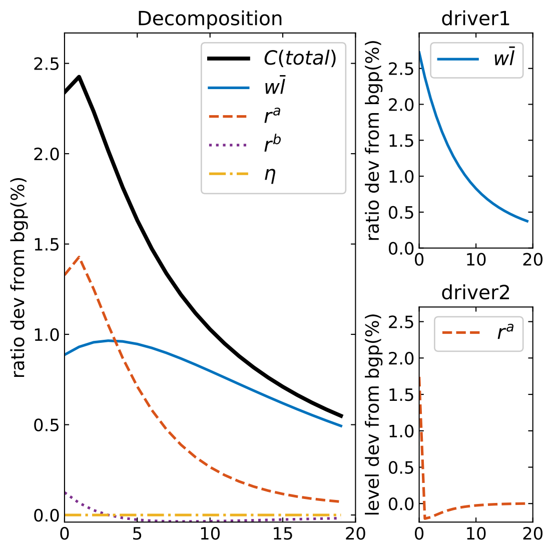
Notes: The statistics are computed under each posterior draw, and their means and standard deviations over the posterior distribution are reported in this table. The numbers in parentheses are the posterior standard deviations.

recalibration. These results verify that all the main observations from variance change decomposition and consumption response decomposition discussed in the main text remain unchanged.

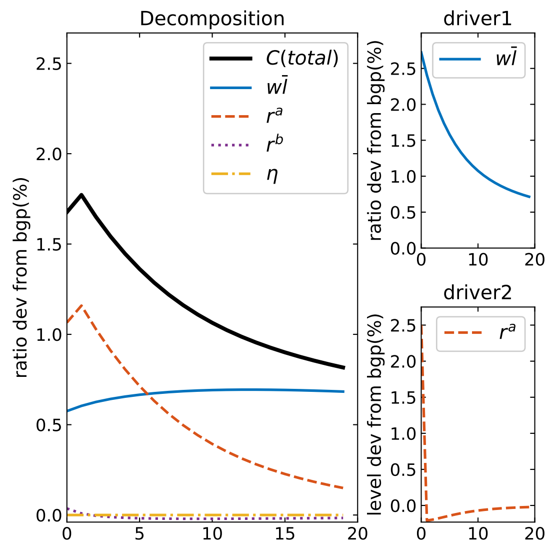
Table C.4: Variance Change Decomposition under Broader Recalibration (from Baseline to Counterfactual)

	$\Delta \log Y_t$	$\Delta \log C_t^{msd}$
stationary productivity shock (z_t)	-0.012	-0.207
	(0.000)	(0.021)
trend shock (g_t)	-0.011	0.049
	(0.008)	(0.024)
interest rate shock (μ_t)	0.000	-0.001
	(0.000)	(0.001)
illiquidity shock (η_t)	-0.001	-0.296
	(0.001)	(0.050)
investment shock (ν_t)	-0.000	-0.049
	(0.000)	(0.020)
variance change (in ratio)	-0.025	-0.504
	(0.008)	(0.049)

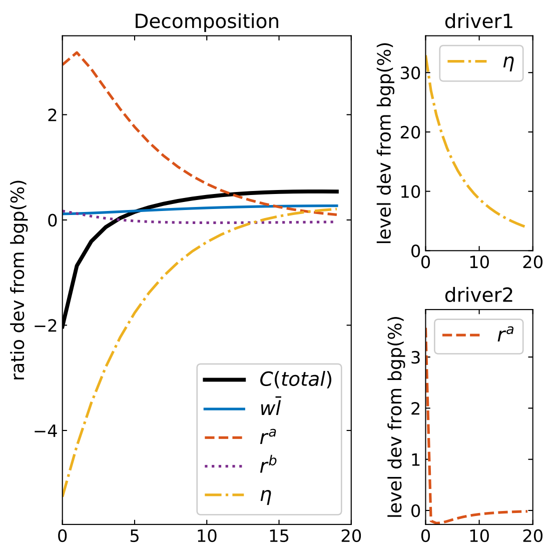
Notes: The last row reports the fraction of [(variance change from the baseline economy to the counterfactual economy) / (variance in the baseline economy)]. The first five rows report the fraction of [(variance change generated by each shock) / (variance in the baseline economy)], in which the denominator is the variance generated by all shocks (*i.e.*, the same denominator used in the fraction reported in the last row.) By construction, the last row is the sum of the first five rows. The statistics are computed under each posterior draw, and their means and standard deviations over the posterior distribution are reported in this table. The numbers in parentheses are the posterior standard deviations.



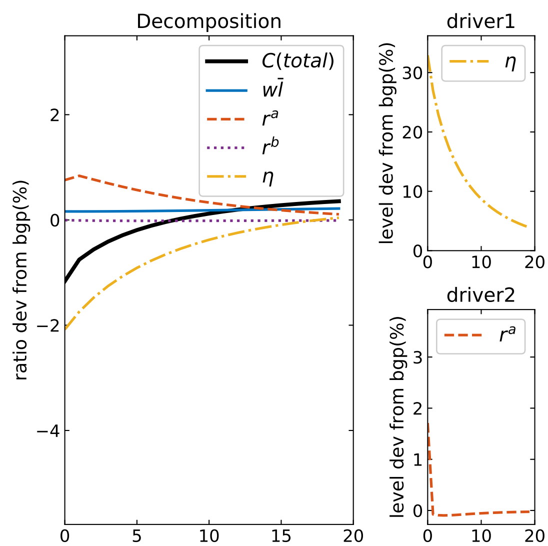
(a) Baseline, z-shock



(b) Counterfactual, z-shock



(c) Baseline, η-shock



(d) Counterfactual, η-shock

Figure C.5: Decomposition of the Consumption Responses to the z-shock and η-shock under Broader Recalibration

Notes: Panels C.5a, C.5b, C.5c, and C.5d present the consumption response decomposition with respect to stationary productivity shocks (z) and illiquidity shocks (η) in the baseline economy and the counterfactual economy, respectively. Each panel consists of three subplots, where the large subplot on the left shows the total consumption response as well as decomposed consumption responses to each driver of $\{w_t\bar{l}_t, r_t^a, r_t^b, \eta_t\}_{t=0}^{\infty}$, and the other two small subplots on the right show the equilibrium paths of the two main drivers after the shock. The consumption responses are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure.

C.5 Impulse Response Functions (IRFs)

C.5.1 Baseline Economy

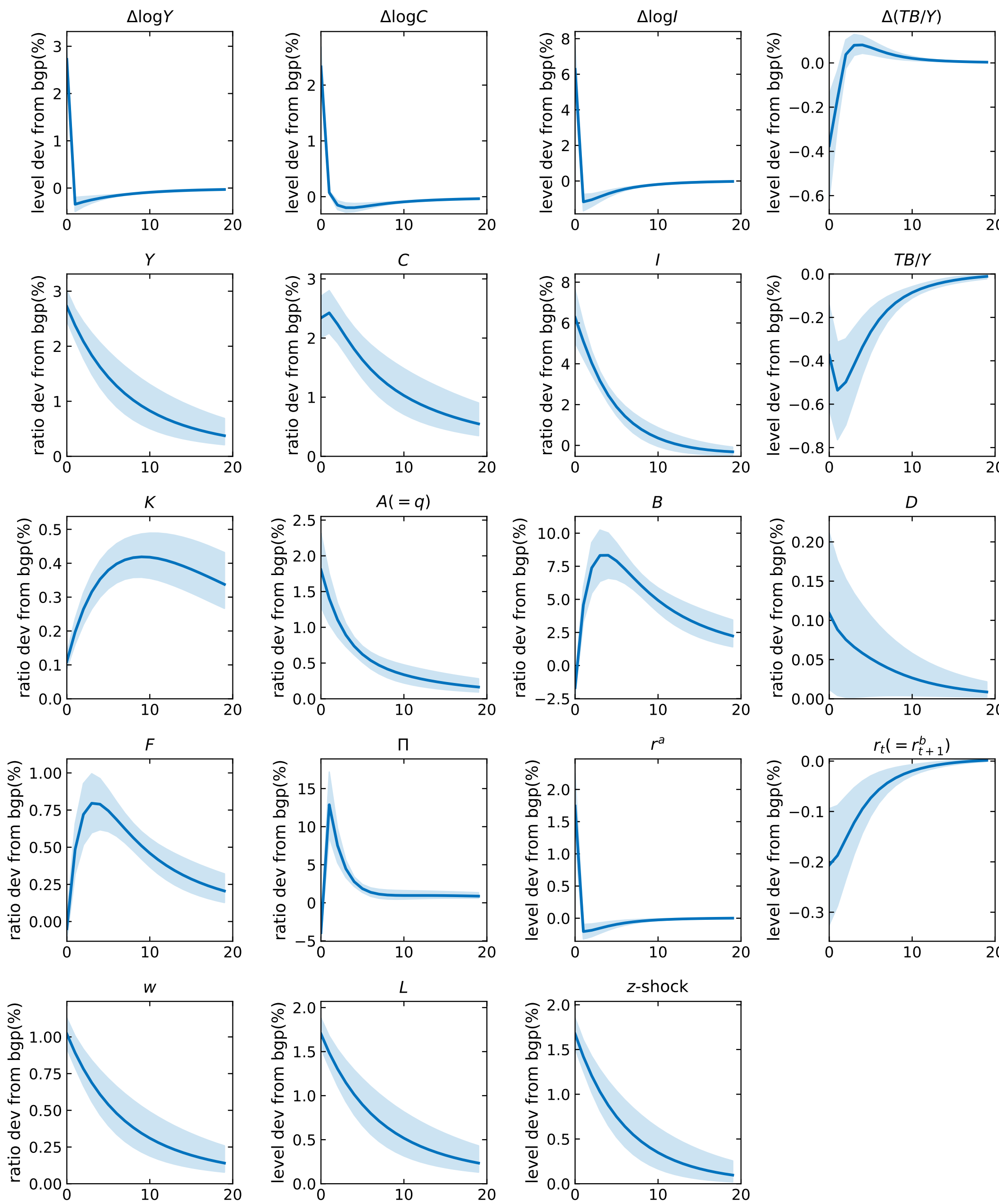


Figure C.6: IRFs to a 1 S.D. Stationary Productivity Shock (z): Baseline Economy

Notes: In each plot, the blue solid line represents the impulse responses in terms of the deviation from the balanced growth path to a one-standard-deviation shock. The impulse responses are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure. The shaded area in each plot represents 90% credible bands over the posterior distribution.

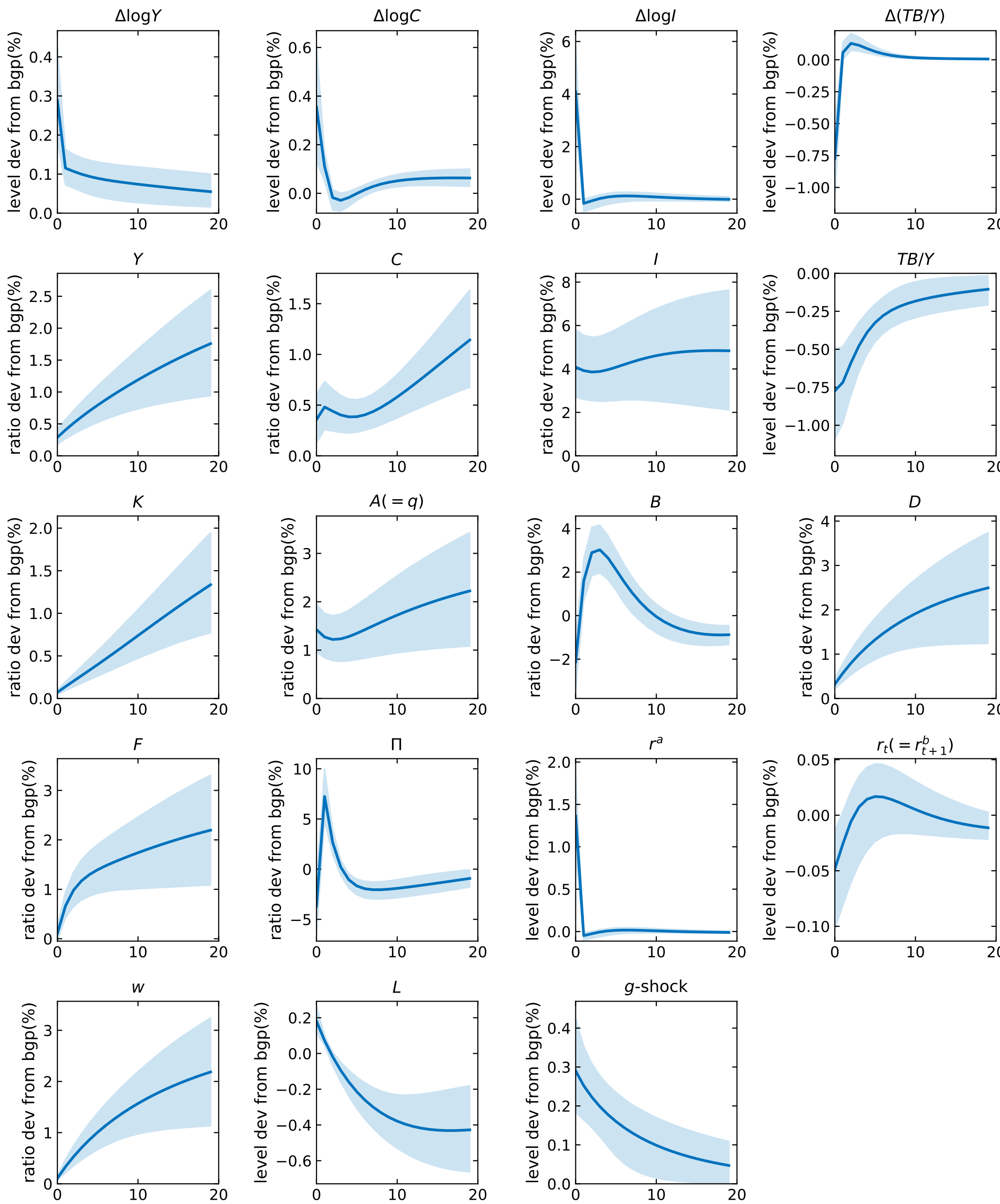


Figure C.7: IRFs to a 1 S.D. Trend Shock (g): Baseline Economy

Notes: In each plot, the blue solid line represents the impulse responses in terms of the deviation from the balanced growth path to a one-standard-deviation shock. The impulse responses are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure. The shaded area in each plot represents 90% credible bands over the posterior distribution.

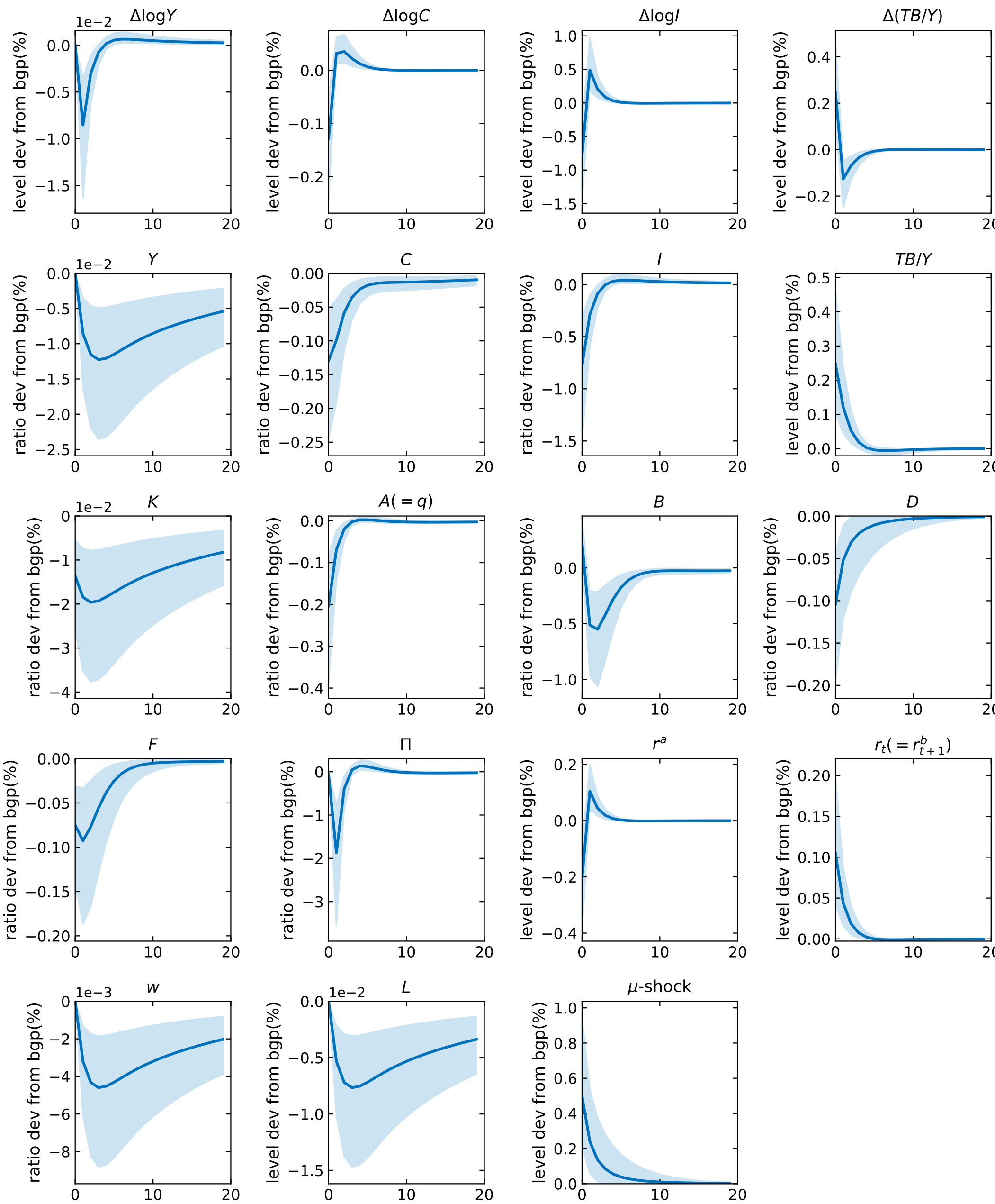


Figure C.8: IRFs to a 1 S.D. Interest Rate Shock (μ): Baseline Economy

Notes: In each plot, the blue solid line represents the impulse responses in terms of the deviation from the balanced growth path to a one-standard-deviation shock. The impulse responses are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure. The shaded area in each plot represents 90% credible bands over the posterior distribution.

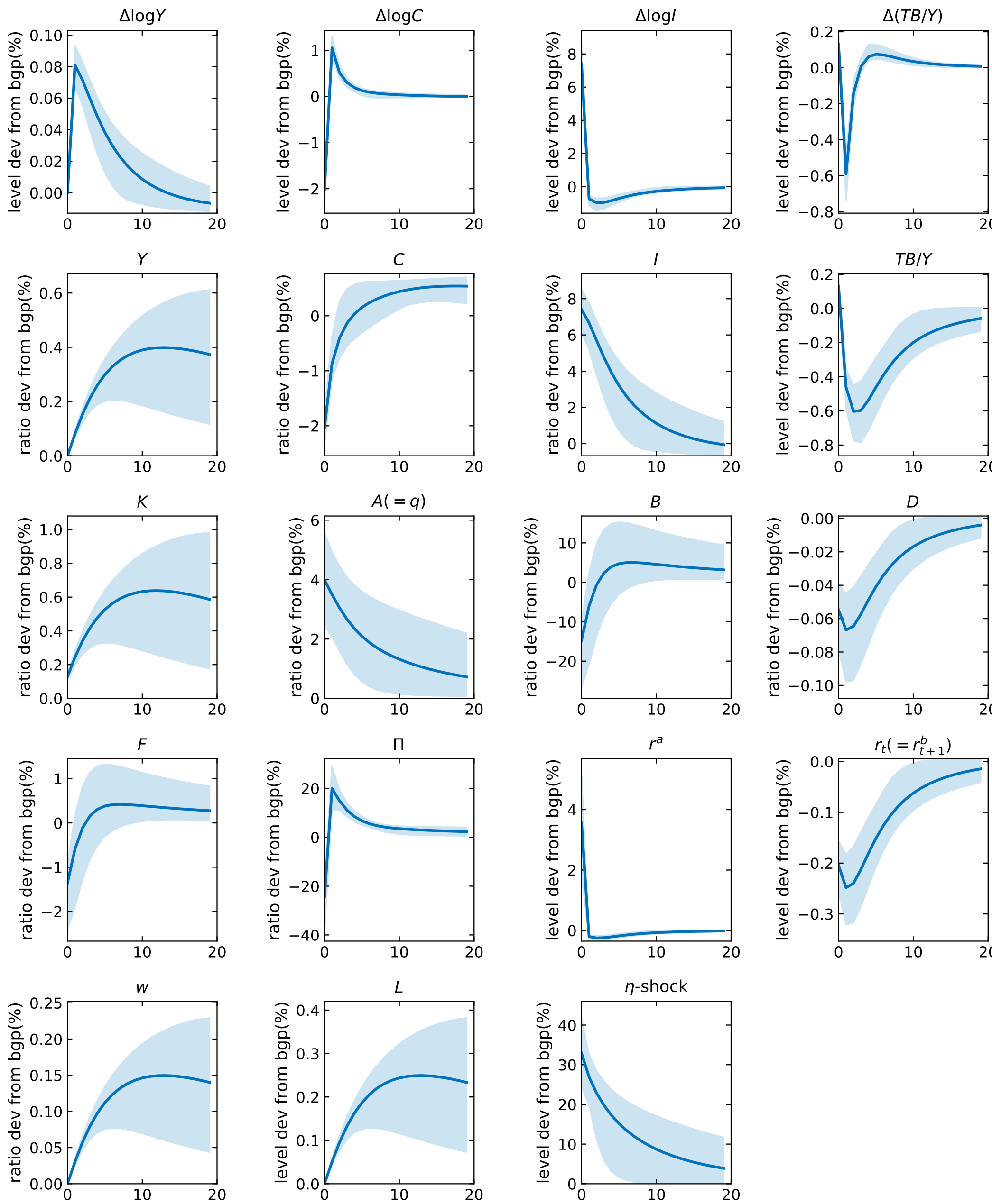


Figure C.9: IRFs to a 1 S.D. Illiquidity Shock (η): Baseline Economy

Notes: In each plot, the blue solid line represents the impulse responses in terms of the deviation from the balanced growth path to a one-standard-deviation shock. The impulse responses are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure. The shaded area in each plot represents 90% credible bands over the posterior distribution.

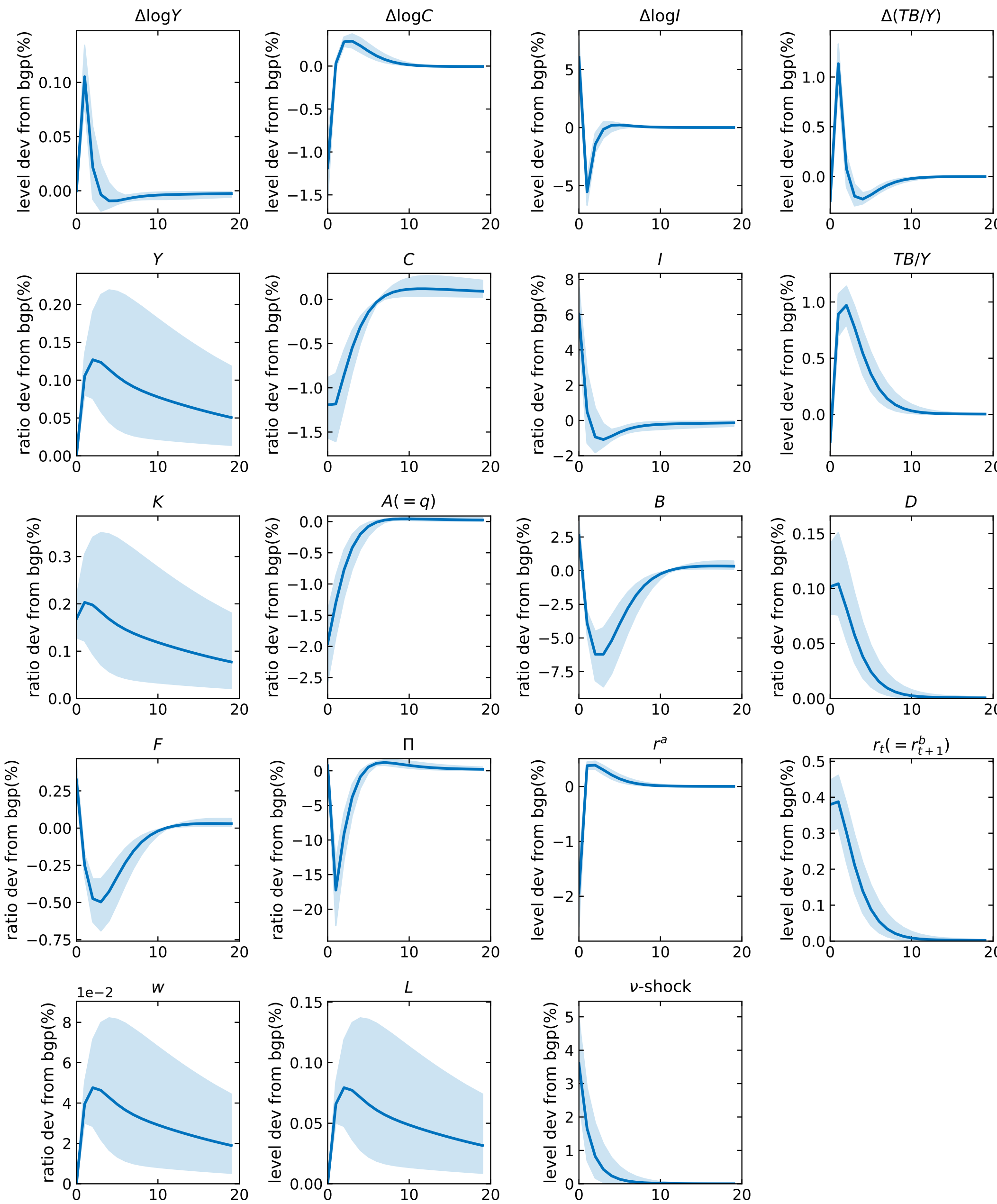


Figure C.10: IRFs to a 1 S.D. Investment Shock (ν): Baseline Economy

Notes: In each plot, the blue solid line represents the impulse responses in terms of the deviation from the balanced growth path to a one-standard-deviation shock. The impulse responses are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure. The shaded area in each plot represents 90% credible bands over the posterior distribution.

C.5.2 Baseline vs Counterfactual

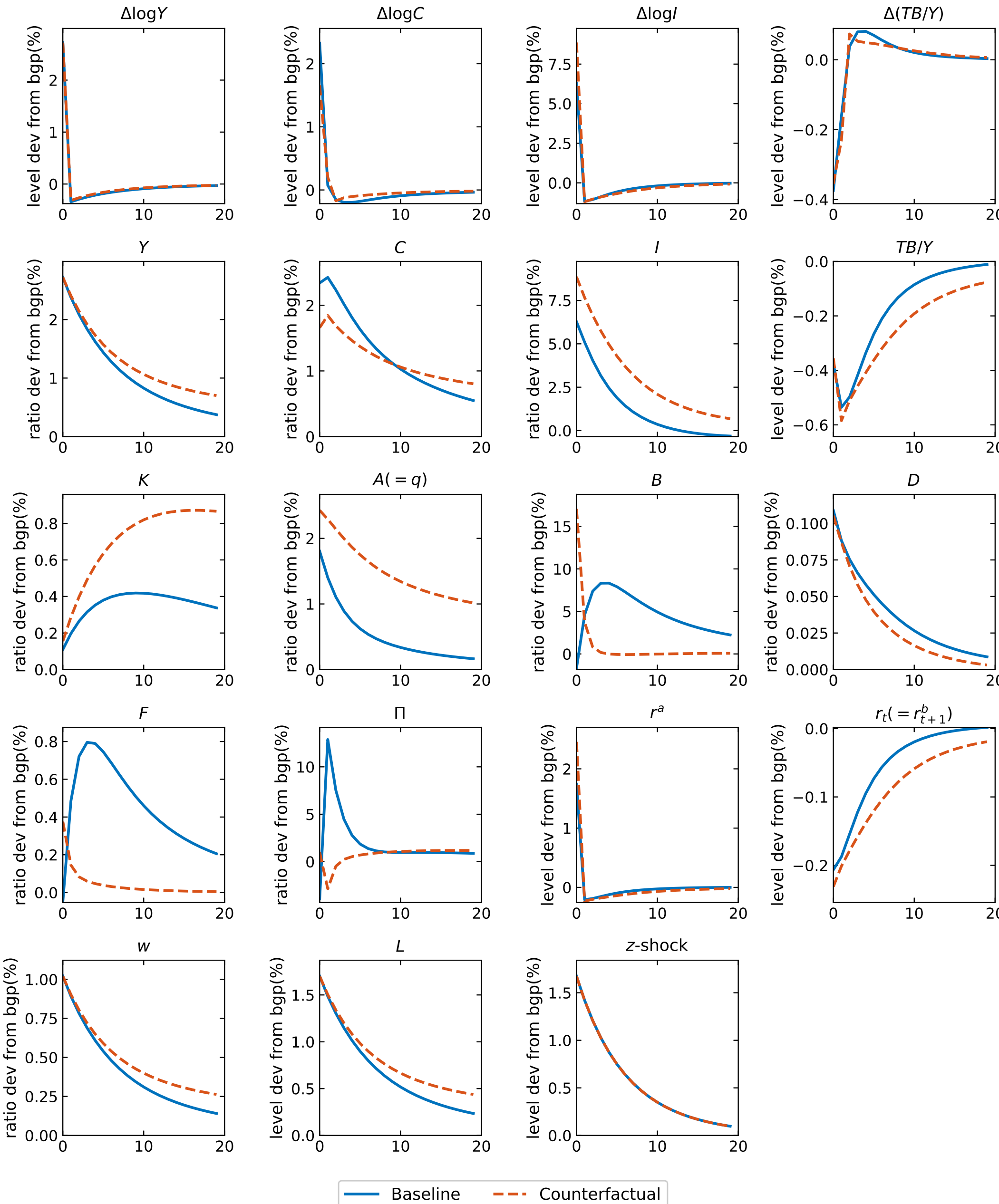


Figure C.11: IRFs to a 1 S.D. Stationary Productivity Shock (z): Baseline vs Counterfactual

Notes: In each plot, the blue solid line and the red dashed line represent the impulse responses in terms of the deviation from the balanced growth path to a one-standard-deviation shock in the baseline economy and the counterfactual economy, respectively. The impulse responses are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure.

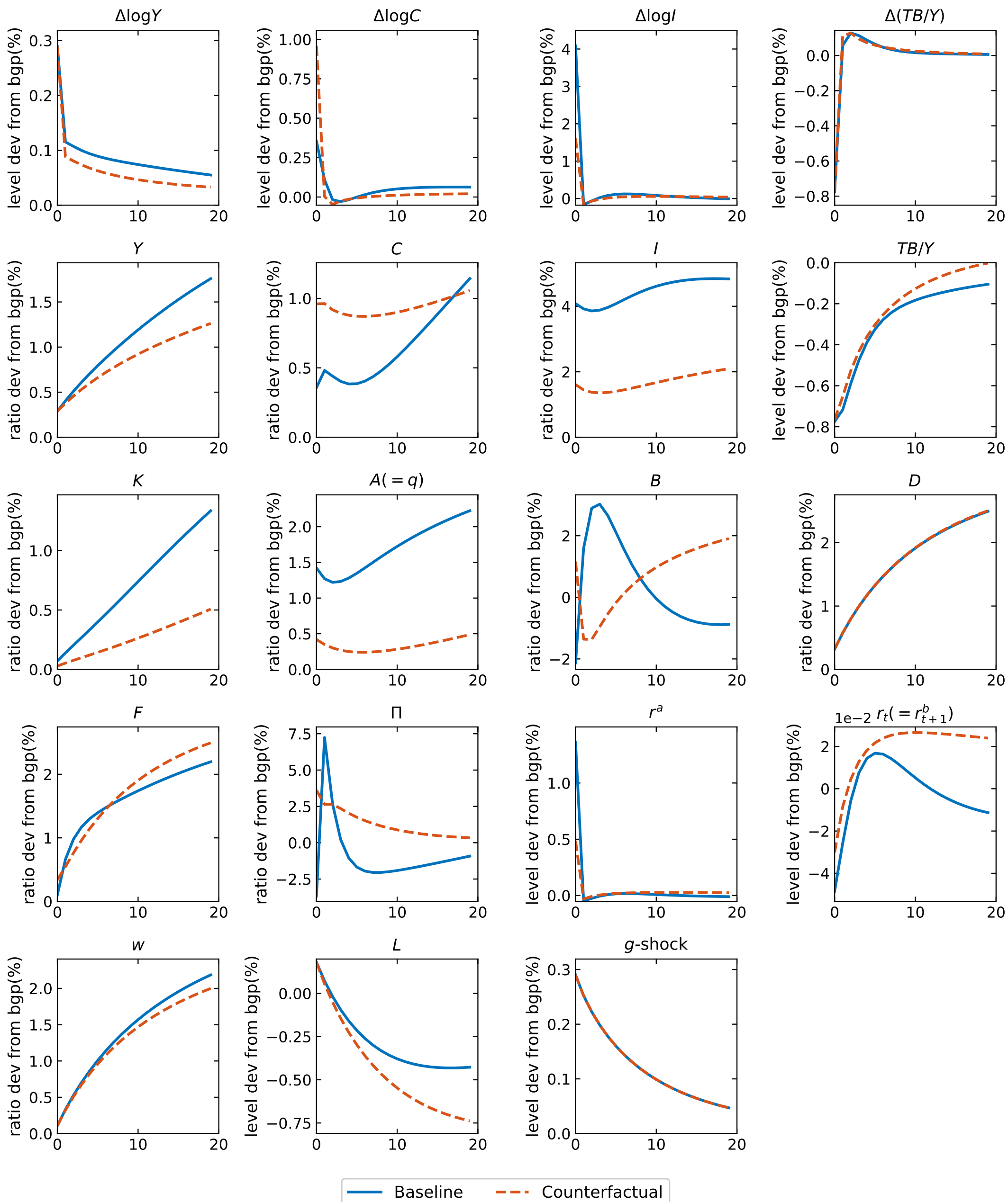


Figure C.12: IRFs to a 1 S.D. Trend Shock (g): Baseline vs Counterfactual

Notes: In each plot, the blue solid line and the red dashed line represent the impulse responses in terms of the deviation from the balanced growth path to a one-standard-deviation shock in the baseline economy and the counterfactual economy, respectively. The impulse responses are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure.

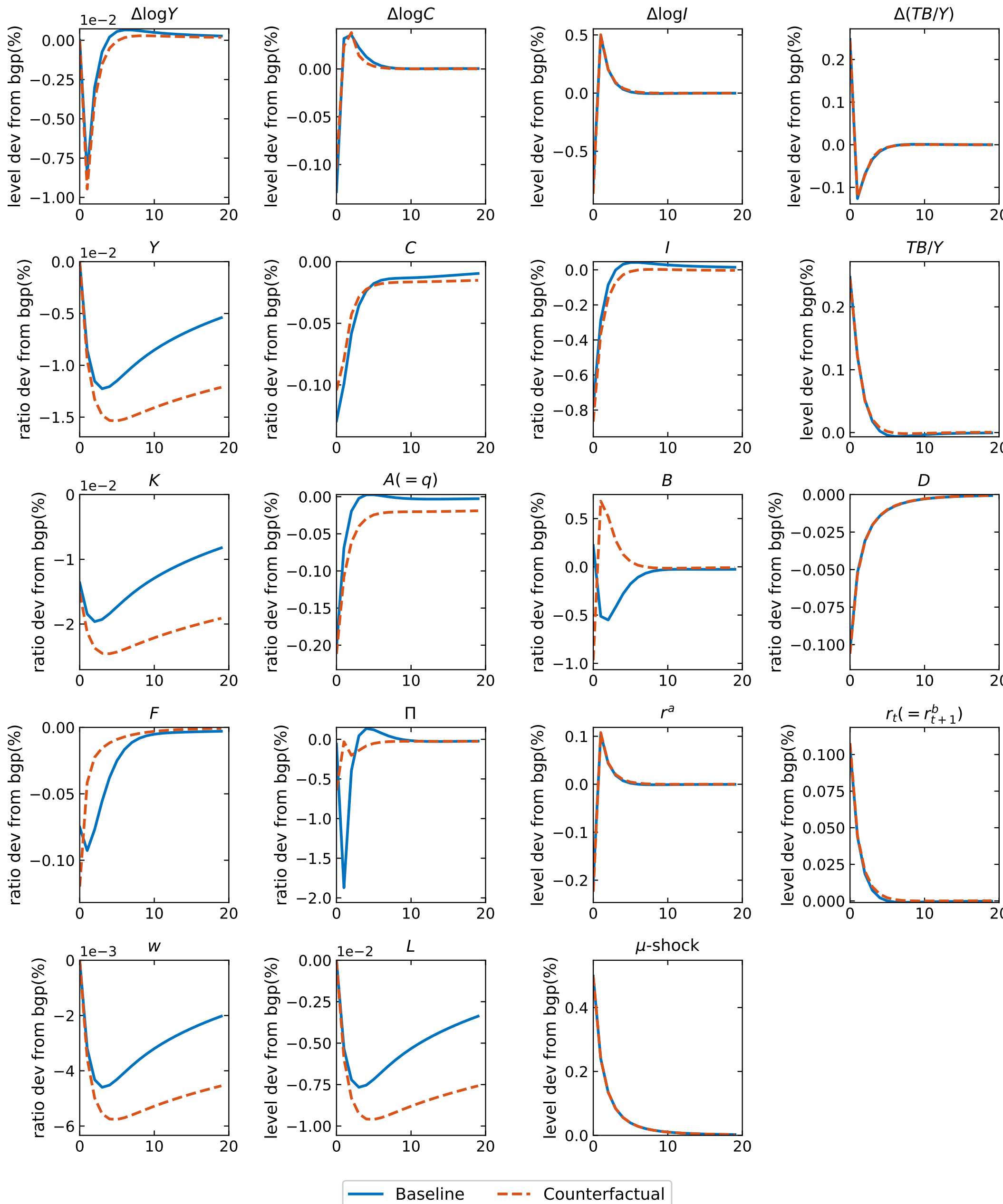


Figure C.13: IRFs to a 1 S.D. Interest Rate Shock (μ): Baseline vs Counterfactual

Notes: In each plot, the blue solid line and the red dashed line represent the impulse responses in terms of the deviation from the balanced growth path to a one-standard-deviation shock in the baseline economy and the counterfactual economy, respectively. The impulse responses are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure.

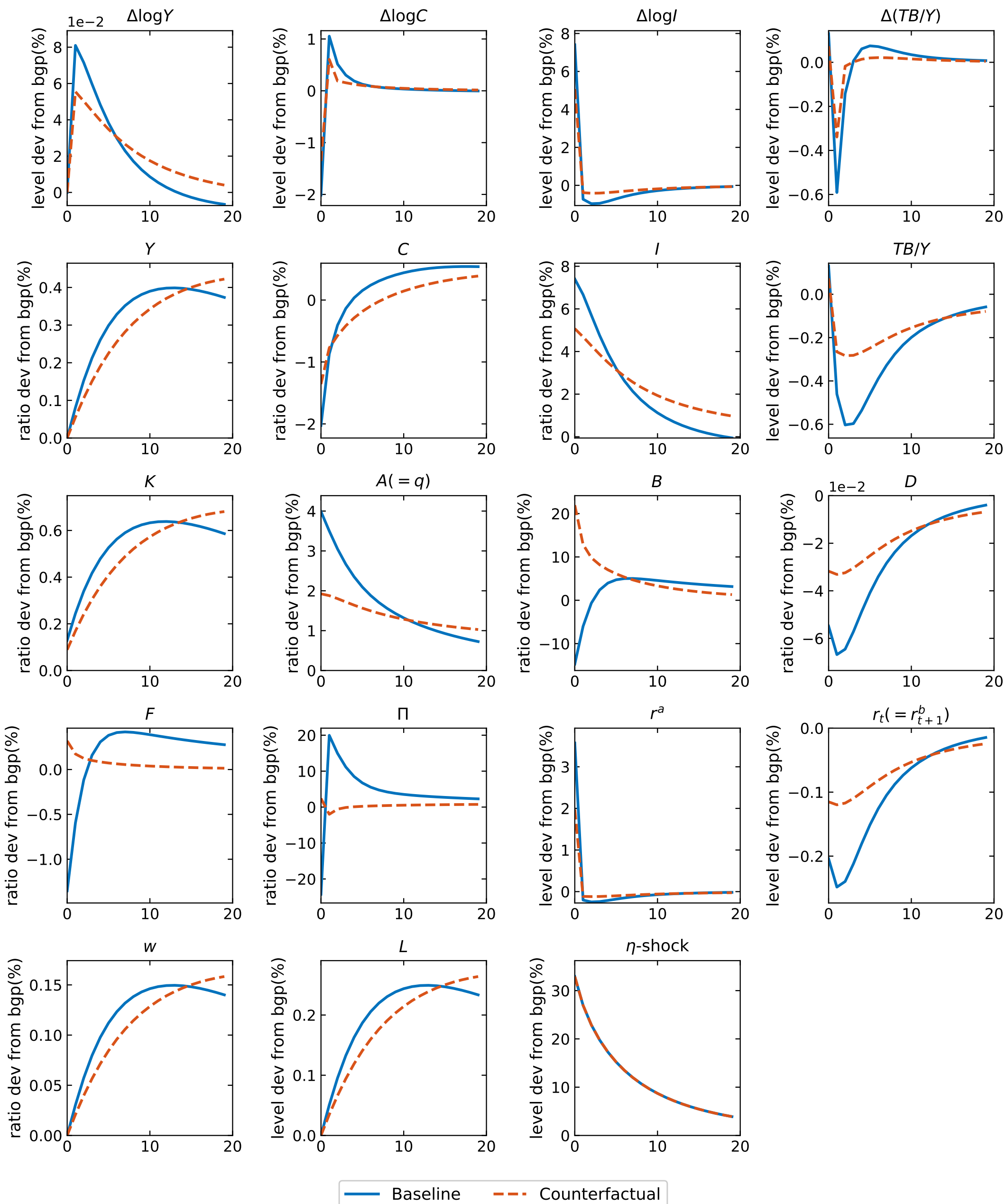


Figure C.14: IRFs to a 1 S.D. Illiquidity Shock (η): Baseline vs Counterfactual

Notes: In each plot, the blue solid line and the red dashed line represent the impulse responses in terms of the deviation from the balanced growth path to a one-standard-deviation shock in the baseline economy and the counterfactual economy, respectively. The impulse responses are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure.

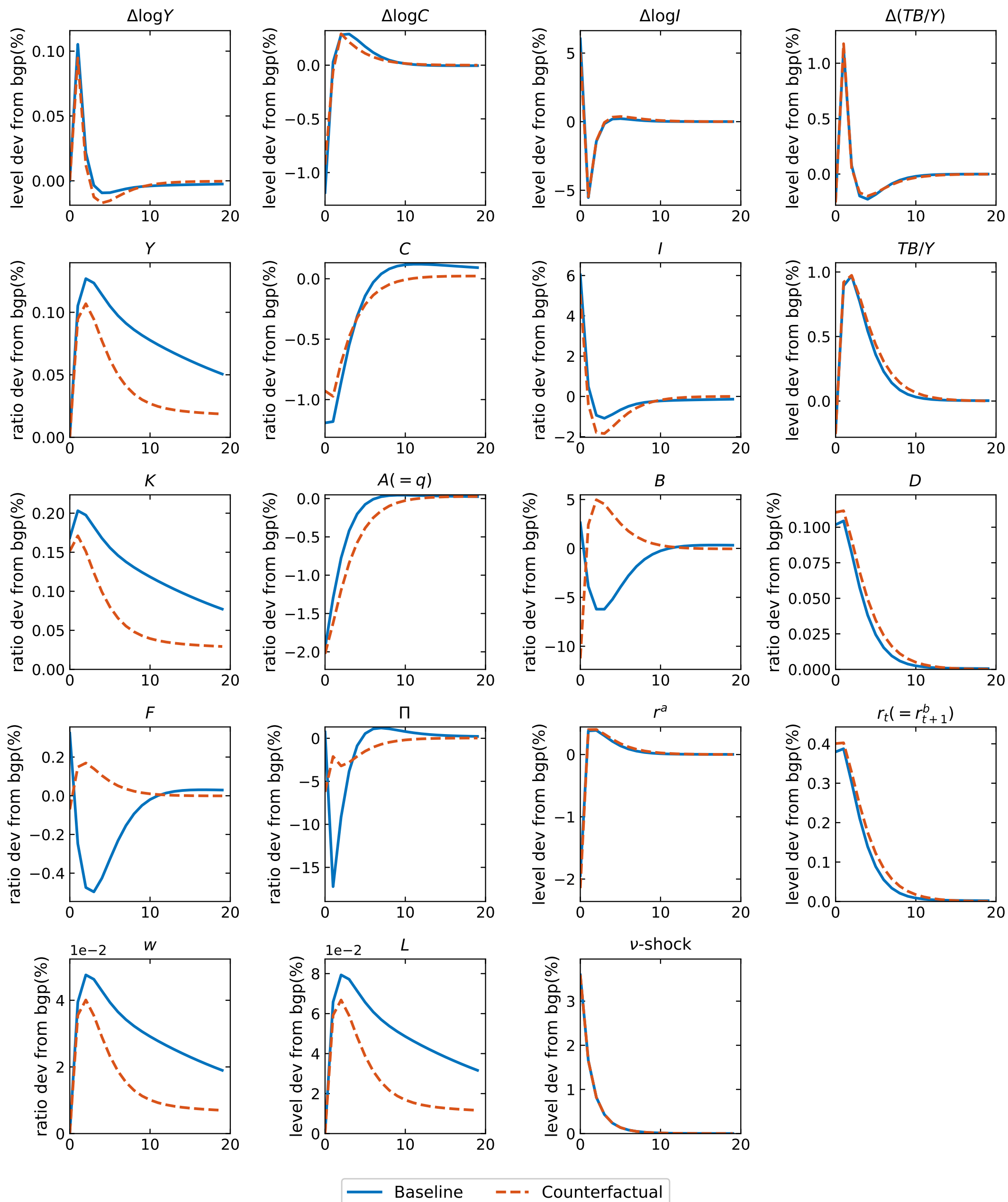


Figure C.15: IRFs to a 1 S.D. Investment Shock (ν): Baseline vs Counterfactual

Notes: In each plot, the blue solid line and the red dashed line represent the impulse responses in terms of the deviation from the balanced growth path to a one-standard-deviation shock in the baseline economy and the counterfactual economy, respectively. The impulse responses are computed under each posterior draw, and their means over the posterior distribution are plotted in this figure.